

New upper and lower bounds for randomized and quantum Local Search*

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Abstract

Local Search problem, which finds a local minimum of a black-box function on a given graph, is of both practical and theoretical importance to combinatorial optimization, complexity theory and many other areas in theoretical computer science. In this paper, we study the problem in the randomized and quantum query models and give new lower and upper bound techniques in both models.

The lower bound technique works for any graph that contains a product graph as a subgraph. Applying it to the Boolean hypercube $\{0, 1\}^n$ and the constant dimensional grids $[n]^d$, two particular product graphs that recently drew much attention, we get the following tight results:

$$\begin{aligned} RLS(\{0, 1\}^n) &= \Theta(2^{n/2}n^{1/2}), & QLS(\{0, 1\}^n) &= \Theta(2^{n/3}n^{1/6}), \\ RLS([n]^d) &= \Theta(n^{d/2}) \text{ for } d \geq 4, & QLS([n]^d) &= \Theta(n^{d/3}) \text{ for } d \geq 6. \end{aligned}$$

Here $RLS(G)$ and $QLS(G)$ are the randomized and quantum query complexities of Local Search on G , respectively. These improve the previous results by Aaronson [2], Ambainis (unpublished) and Santha and Szegedy[20].

Our new algorithms work well when the underlying graph expands slowly. As an application to $[n]^2$, a new quantum algorithm using $O(\sqrt{n}(\log \log n)^{1.5})$ queries is given. This improves the previous best known upper bound of $O(n^{2/3})$ (Aaronson, [2]), and implies that Local Search on grids exhibits different properties in low dimensions.

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1 Introduction

Many important combinatorial optimization problems arising in both theory and practice are **NP**-hard, which forces people to resort to heuristic searches in practice. One popular approach is Local Search, by which one first defines a *neighborhood structure*, then finds a solution that is locally optimal with respect to this neighborhood structure. In the past two decades, Local Search approach has been extensively developed and “has reinforced its position as a standard approach in combinatorial optimization” in practice [1]. Besides the practical applications, the problem also has many connections to the complexity theory, especially to the complexity classes **PLS**¹ and **TFNP**². For example, the 2SAT-FLIP problem is Local Search on the Boolean hypercube graph $\{0, 1\}^n$, with the objective function being the sum of the weights of the clauses that the truth assignment $x \in \{0, 1\}^n$ satisfies. This problem is complete in **PLS**, implying that the Boolean hypercube $\{0, 1\}^n$ has a central position in the studies of Local Search. Local Search is also related to physical systems including folding proteins and to the quantum adiabatic algorithms [2]. We refer readers to the papers [2, 19, 20] for more discussions and the book [3] for a comprehensive introduction.

Precisely, Local Search on an undirected graph $G = (V, E)$ is defined as follows. Given a function $f : V \rightarrow \mathbb{N}$, find a vertex $v \in V$ such that $f(v) \leq f(w)$ for all neighbors w of v . A class of *generic algorithms* that has been widely used in practice is as follows: we first set out with an initial point $v \in V$, then repeatedly search a better/best neighbor until it reaches a local minimum. Though empirically this class of algorithms work very well in most applications, relatively few theoretical results are known about how good the generic algorithms are, especially for the randomized (and quantum) algorithms.

Among models for the theoretical studies, the query model has drawn much attention [2, 4, 5, 16, 17, 20]. In this model, f is given by a black-box, *i.e.* $f(v)$ can be accessed by querying v . We only care about the number of queries made, and all other computations are free. If we are allowed to toss coins to decide the next query, then we have randomized query algorithm. If we are allowed use quantum mechanics to query all the positions (and get corresponding answers) in superposition, then we have quantum query algorithms. The deterministic, randomized and quantum query complexities, are the minimum number of queries needed to compute the function by a deterministic, randomized and quantum query algorithm, respectively. We use $RLS(G)$ and $QLS(G)$ to denote the randomized and quantum query complexities of Local Search on graph G , respectively. Previous upper bounds on a general N -vertex graph G are $RLS(G) = O(\sqrt{N\delta})$ by Aldous [4] and $QLS(G) = O(N^{1/3}\delta^{1/6})$ by Aaronson [2], where δ is the maximum degree of G . Both algorithms actually fall into the category of generic algorithms mentioned above, with the initial point picked as a best one over a certain number of random samples. Immediately, two questions can be asked:

1. On what graphs are these simple algorithms optimal?
2. For other graphs, what better algorithms can we have?

Clearly the first one is a lower bound question and the second one is an upper bound question.

Previously for lower bounds, Aaronson [2] showed the following results on two special classes of graphs: the Boolean hypercube $\{0, 1\}^n$ and the constant dimensional grid $[n]^d$:

$$RLS(\{0, 1\}^n) = \Omega(2^{n/2}/n^2), \quad QLS(\{0, 1\}^n) = \Omega(2^{n/4}/n); \quad (1)$$

$$RLS([n]^d) = \Omega(n^{d/2-1}/\log n), \quad QLS([n]^d) = \Omega(n^{d/4-1/2}/\sqrt{\log n}). \quad (2)$$

It has also been shown that $QLS([n]^2) = \Omega(n^{1/4})$ by Santha and Szegedy in [20], besides their main result that the deterministic and the quantum query complexities of Local Search on any graph are polynomially related. However, the question

3. What are the final values of QLS and RLS on $\{0, 1\}^n$ and $[n]^d$?

remains an open problem, explicitly stated in an earlier version of [2] and also (partially) in [20].

¹Polynomial Local Search, introduced by Johnson, Papadimitriou, and Yannakakis [14].

²The family of total function problems, introduced by Megiddo and Papadimitriou [18].

In this paper, we answer questions 1 and 2 for large classes of graphs by giving both new lower and upper bound techniques for randomized and quantum query algorithms. As a consequence, we completely solve the question 3, except for a few small d 's where our new bounds also significantly improve the old ones.

Our lower bound technique works for any graph that contains a product graph as a subgraph. For two graphs $G_1 = (V_1, E_1)$ and $G_2 = (V_2, E_2)$, their product $G_1 \times G_2$ is the graph $G = (V, E)$ where $V = V_1 \times V_2$ and

$$E = \{(v_1 \otimes v_2, v'_1 \otimes v_2) : (v_1, v'_1) \in E_1, v_2 \in V_2\} \cup \{(v_1 \otimes v_2, v_1 \otimes v'_2) : (v_2, v'_2) \in E_2, v_1 \in V_1\} \quad (3)$$

We will also use the notion of random walk on graphs to state the theorem. Given a graph $G = (V, E)$, a random walk is a mapping $W : V \rightarrow 2^V$ where $W(u) \subseteq \{u\} \cup \{v : (u, v) \in E\}$. Intuitively, at each step the random walk W goes from the current vertex u to a uniformly random vertex in $W(u)$. The walk W is *regular* if $|W(u)| = c$ for each $u \in V$. Denote by $p(u, v, t)$ the probability that the random walk starting at u is at v after exactly t steps. Let $p_t = \max_{u,v} p(u, v, t)$. The following theorem is a special case of the general one (Theorem 9) in Section 3.

Theorem 1 *Suppose G contains the product graph $G_1 \times G_2$ as a subgraph, and L is the length of the longest self-avoiding path in G_2 . Let $T = \lfloor L/2 \rfloor$, then for any regular random walk W on G_1 , we have*

$$RLS(G) = \Omega\left(\frac{T}{\sum_{t=1}^T p_t}\right), \quad QLS(G) = \Omega\left(\frac{T}{\sum_{t=1}^T \sqrt{p_t}}\right).$$

The proof uses the quantum adversary method, which was originally proposed by Ambainis [7] and later generalized in different ways [6, 8, 15, 23]. Recently Spalek and Szegedy made the picture clear by showing that all these generalizations are equivalent in power [21]. On the other hand, in proving a particular problem, some of the methods might be easier to apply than the others. In our case, the technique in [23], which generalizes the one in [6] slightly in the form though, turns out to work very well. Our proofs for the randomized lower bounds will use the relational adversary method, which was proposed by Aaronson [2] inspired by the quantum adversary method.

Both the quantum adversary method and the relational adversary method are parameterized by input sets and weight functions of input pairs. While previous works [2, 20] also use random walks on graphs, a key innovation that distinguishes our work from the previous ones and yields better lower bounds is that we decompose the graph into two parts, the tensor product of which is the original graph. We perform the random walk only in one part, and perform a simple one-way walk in a self-avoiding path in the other part, which serves as a “clock” to record the number of steps taken by the random walk in the first part. The tensor product of these two walks is a random path in the original graph. A big advantage of adding a clock is that the “passing probability”, the probability that the random path *passes* a vertex v *within* T steps, is now the “hitting probability”, the probability that the random walk in the first graph *hits* v *after* exactly t steps, because the time elapses one-way and never comes back. The fact that the hitting probability is much smaller than the passing probability enables us to achieve the better lower bounds. Another advantage of the clock is that since the walk in the second part is self-avoiding, the resulting random path in the original graph is self-avoiding too, which makes the analysis much easier.

Applying it to the two graphs $\{0, 1\}^n$ and $[n]^d$, we improve previous results and show tight bounds on both RLS and QLS (except for a few cases in the low dimensional grids).

Theorem 2

$$RLS(\{0, 1\}^n) = \Theta(2^{n/2} n^{1/2}), \quad QLS(\{0, 1\}^n) = \Theta(2^{n/3} n^{1/6}). \quad (4)$$

Theorem 3

$$RLS([n]^d) = \begin{cases} \Theta(n^{d/2}) & \text{if } d \geq 4, \\ \Omega((n^3/\log n)^{1/2}) & \text{if } d = 3, \\ \Omega(n^{2/3}) & \text{if } d = 2. \end{cases} \quad QLS([n]^d) = \begin{cases} \Theta(n^{d/3}) & \text{if } d \geq 6, \\ \Omega((n^5/\log n)^{1/3}) & \text{if } d = 5, \\ \Omega(n^{6/5}) & \text{if } d = 4, \\ \Omega(n^{3/4}) & \text{if } d = 3, \\ \Omega(n^{2/5}) & \text{if } d = 2. \end{cases} \quad (5)$$

It is worth to note that to apply Theorem 1, we need not only know the mixing time of the random walk in G_1 , but also know *its behavior before mixing*. So the applications are not simply using standard upper bounds on the mixing times, but involving heavy analysis on the whole mixing processes.

When proving Theorem 3 by Theorem 1, one difficulty arises: to decompose the grid $[n]^d$ into two parts $[n]^m$ and $[n]^{d-m}$, we implicitly require that m is an integer. This lets us get lower bounds weaker than Theorem 3, especially for low dimension cases. We get around this problem by cutting one of the m dimensions into many blocks, and use different block to distinguish different time windows. Between adjacent blocks are pairwise disjoint path segments, which thus thread all the blocks into a very long one. Using this technique, we can apply Theorem 1 for any read-number dimension $m \leq d - 1$.

In the second part of the paper, we consider upper bounds for Local Search. While the generic algorithms [2, 4] are simple and proven to be optimal for many graphs such as the ones mentioned above, they are far from optimal for some other graphs. For example, it is not hard to see an $O(\log N)$ *deterministic* algorithm for the line graph G . Therefore, a natural question is to characterize those graphs on which Local Search is easy. It turns out that the expansion speed plays a key role. For a graph $G = (V, E)$, the distance $|u - v|$ between two vertices u and v is the length of the shortest path connecting them. (Here the length of a path is the number of edges on the path.) Let $c(k) = \max_{v \in V} |\{u : |u - v| \leq k\}|$. Apparently, the smaller $c(k)$ is, the more slowly the graph expands. (Actually $c(k)$ is an upper bound of the standard definition of the expanding speed.) As a special case of Theorem 12 in Section 5, the following upper bounds in terms of $c(k)$ hold.

Theorem 4 *If $c(k) = O(k^\alpha)$ for some constant $\alpha \geq 1$, then*

$$RLS(G) = \begin{cases} O(d^{\alpha-1} \log \log d) & \text{if } \alpha > 1, \\ O(\log d \log \log d) & \text{if } \alpha = 1. \end{cases} \quad QLS(G) = \begin{cases} O(d^{\frac{\alpha-1}{2}} (\log \log d)^{1.5}) & \text{if } \alpha > 1, \\ O(\log d \log \log d) & \text{if } \alpha = 1. \end{cases} \quad (6)$$

where d is the diameter of the graph G .

As a special case, on the line graph we get $\alpha = 1$ and hence $RLS = O(\log n \log \log n)$, which helps to explain why Local Search on the line graph is easy. Also, it immediately gives a new upper bound for $QLS([n]^2)$ as follows. Together with Theorem 3, this implies that Local Search on grids exhibits different properties in low dimensions.

Theorem 5 $QLS([n]^2) = O(\sqrt{n}(\log \log n)^{1.5})$

Other related results. After the preliminary version of this paper appeared, Verhoeven independently showed an upper bound in terms of the genus of the graph [22], giving an $O(\sqrt{n} \log \log n)$ quantum algorithm for $[n]^2$. There is also an unpublished result on $QLS(\{0, 1\}^n)$: it is mentioned in [2] that Ambainis showed $QLS(\{0, 1\}^n) = \Omega(2^{n/3}/n^{O(1)})$.³

³Another unpublished result was mentioned in [20] that Verhoeven showed $RLS([n]^2) = \Omega(n^{1-\delta})$ for any constant $\delta > 0$. But according to an author of [20], the proof was never written up and this question should be considered now to be still open.

2 Preliminaries and notations

We use $[M]$ to denote the set $\{1, 2, \dots, M\}$. For an n -bit binary string $x = x_0 \dots x_{n-1} \in \{0, 1\}^n$, let $x^{(i)} = x_0 \dots x_{i-1}(1 - x_i)x_{i+1} \dots x_{n-1}$ be the string obtained by flipping the coordinate i .

For graphs $G_1 = (V_1, E_1)$ and $G_2 = (V_2, E_2)$, we say that G_1 is a subgraph of G_2 if $V_1 \subseteq V_2$ and $E_1 \subseteq E_2$. Apparently, any local optimum in G_2 is also a local optimum in G_1 (but not the other way around in general), therefore any lower bound for G_1 is also a lower bound for G_2 .

We will use $v_1 \otimes v_2$ to range over the set $V_1 \times V_2$. There are various ways to define a product graph $G_1 \times G_2 = (V_1 \times V_2, E)$ by different choices of E . Three possibilities are

1. $E = \{(v_1 \otimes v_2, v'_1 \otimes v'_2) : (v_1, v'_1) \in E_1, v_2 \in V_2\} \cup \{(v_1 \otimes v_2, v_1 \otimes v'_2) : (v_2, v'_2) \in E_2, v_1 \in V_1\}$;
2. $E' = \{(v_1 \otimes v_2, v'_1 \otimes v'_2) : (v_1, v'_1) \in E_1 \cup I_{V_1} \text{ and } (v_2, v'_2) \in E_2 \cup I_{V_2}\} - I_{V_1 \times V_2}$, where $I_V = \{(v, v) : v \in V\}$;
3. $E'' = \{(v_1 \otimes v_2, v'_1 \otimes v'_2) : (v_1, v'_1) \in E_1 \cup I_{V_1} \text{ or } (v_2, v'_2) \in E_2 \cup I_{V_2}\} - I_{V_1 \times V_2}$.

It is clear that $E \subseteq E' \subseteq E''$, and our lower bound theorem will use the first definition E , making the theorem as general as possible.

A path X in a graph $G = (V, E)$ is a sequence (v_1, \dots, v_l) of vertices such that for any pair (v_i, v_{i+1}) of vertices, either $v_i = v_{i+1}$ or $(v_i, v_{i+1}) \in E$. We use $\text{set}(X)$ to denote the set of distinct vertices on path X . A path is self-avoiding if v_1, \dots, v_l are all distinct. The length of a path (v_1, \dots, v_l) is $l - 1$. For two vertices $u, v \in V$, the distance $|u - v|_G$ is the length of a shortest path from u to v . The subscript G may be omitted if no confusion is caused.

The (k, l) -hypercube $G_{k,l} = (V, E)$ where $V = [k]^l$ and whose edge set is $E = \{(u, v) : \exists i \in \{0, \dots, l-1\}, \text{ s.t. } |u_i - v_i| = 1, \text{ and } u_j = v_j, \forall j \neq i\}$. Sometimes we abuse the notation by using $[k]^l$ to denote $G_{k,l}$. Note that both the Boolean hypercube and the constant dimension grid are special hypercubes.⁴

In an N -vertex graph $G = (V, E)$, a Hamilton path is a path $X = (v_1, \dots, v_N)$ such that $(v_i, v_{i+1}) \in E$ for any $i \in [N - 1]$ and $\text{set}(X) = V$. It is easy to check by induction that every hypercube $[k]^l$ has a Hamilton path. Actually, for $l = 1$, $[k]$ has a Hamilton path $(1, \dots, k)$. Now suppose $[k]^l$ has a Hamilton path P , then a Hamilton path for $[k]^{l+1}$ can be constructed as follows. First fix the last coordinate to be 1 and go through P , then change the last coordinate to be 2 and go through P in the reverse order, and then change the last coordinate to be 3 and go through P , and so on. For each (k, l) , let $\text{HamPath}_{k,l} = (v_1, \dots, v_N)$ be the Hamilton path constructed as above (where $N = k^l$), and we define the successor function $H_{k,l}(v_i) = v_{i+1}$ for $i \in [N - 1]$.

As mentioned in Section 1, a deterministic query algorithm for a function $f : I^n \rightarrow [M]$ accesses the input $x \in I^n$ only by making queries in the form of “ $x_i = ?$ ”. Each query has cost 1, and all the other computation between queries are free. A randomized query algorithm is the same except that the algorithm can toss coins to decide which variable x_i to ask next. The quantum query model, formally introduced in [9], has a working state in the form of $\sum_{i,a,z} \alpha_{i,a,z} |i, a, z\rangle$. A quantum query on the input x proceeds as follows.

$$\sum_{i,a,z} \alpha_{i,a,z} |i, a, z\rangle \rightarrow \sum_{i,a,z} \alpha_{i,a,z} |i, a \oplus x_i, z\rangle \quad (7)$$

A T -query quantum query algorithm works as a sequence of operations

$$U_0 \rightarrow O_x \rightarrow U_1 \rightarrow O_x \rightarrow \dots \rightarrow U_{T-1} \rightarrow O_x \rightarrow U_T \quad (8)$$

where O_x is as defined above, and each U_t does not depend on the input x . In both randomized and quantum query models, we can allow a double-sided small constant error probability. The deterministic, randomized and quantum query complexities, denoted by $D(f)$, $R_2(f)$ and $Q_2(f)$, are the minimum numbers of queries we need to make in order to compute the function by a deterministic, randomized and quantum query algorithm, respectively. For more details on the query models and the corresponding query complexities, we refer to [10] as an excellent survey.

⁴Here we identify the Boolean hypercube $\{0, 1\}^n$ and $G_{2,n}$ since they are isomorphic.

2.1 One quantum adversary method and the relational adversary method

The quantum adversary method is one of the two powerful tools to prove lower bounds on quantum query complexity; see [13] for an comprehensive survey of this research area. In this paper, we will use the quantum adversary method proposed in [23]. The definition and theorem given here are a little more general than the original ones, but the proof remains unchanged.

Definition 1 Let $F : I^N \rightarrow [M]$ be an N -variate function. Let $R \subseteq I^N \times I^N$ be a relation such that $F(x) \neq F(y)$ for any $(x, y) \in R$. A weight scheme consists of three weight functions $w(x, y) > 0$, $u(x, y, i) > 0$ and $v(x, y, i) > 0$ satisfying $u(x, y, i)v(x, y, i) \geq w^2(x, y)$ for all $(x, y) \in R$ and $i \in [N]$ with $x_i \neq y_i$. We further put

$$w_x = \sum_{y' : (x, y') \in R} w(x, y'), \quad w_y = \sum_{x' : (x', y) \in R} w(x', y) \quad (9)$$

$$u_{x,i} = \sum_{y' : (x, y') \in R, x_i \neq y'_i} u(x, y', i), \quad v_{y,i} = \sum_{x' : (x', y) \in R, x'_i \neq y_i} v(x', y, i). \quad (10)$$

Theorem 6 [Zhang, [23]] For any F, R and any weight scheme w, u, v as in Definition 1, we have

$$Q_2(F) = \Omega \left(\min_{(x,y) \in R, i \in [N]: x_i \neq y_i} \sqrt{\frac{w_x w_y}{u_{x,i} v_{y,i}}} \right) \quad (11)$$

In [2], Aaronson gives a nice technique to get a lower bound for randomized query complexity. We restate it using a similar language of Theorem 6.

Theorem 7 [Aaronson, [2]] Let $F : I^N \rightarrow [M]$ be an N -variate function. Let $R \subseteq I^N \times I^N$ be a relation such that $F(x) \neq F(y)$ for any $(x, y) \in R$. For any weight function $w : R \rightarrow \mathbb{R}^+$, we have

$$R_2(F) = \Omega \left(\min_{(x,y) \in R, i \in [N], x_i \neq y_i} \max \left\{ \frac{w_x}{w_{x,i}}, \frac{w_y}{w_{y,i}} \right\} \right) \quad (12)$$

where

$$w_{x,i} = \sum_{y' : (x, y') \in R, x_i \neq y'_i} w(x, y'), \quad w_{y,i} = \sum_{x' : (x', y) \in R, x'_i \neq y_i} w(x', y). \quad (13)$$

Note that we can think of Theorem 7 as having a weight scheme too, but requiring that $u(x, y, i) = v(x, y, i) = w(x, y)$. This simple observation is used in the proof of Theorem 2 and 3.

3 Lower bounds for Local Search on product graphs

In this section we prove a theorem which is stronger than Theorem 1 due to a relaxation on the conditions of the random walk. Suppose we are given a graph $G = (V, E)$, a starting vertex v_0 and an assignment $W : V \times \mathbb{N} \rightarrow 2^V$ s.t. for each $u \in V$ and $t \in \mathbb{N}$, it holds that $W(u, t) \subseteq \{u\} \cup \{v : (u, v) \in E\}$ and that $|W(u, t)| = c_t$ for some function c of t . Intuitively, W gives the candidates that the walk goes to for the next step, and the random walk (G, v_0, W) on graph G proceeds as follows. It starts at v_0 , and at step $t \in \mathbb{N}$, it goes from the current vertex v_{t-1} to a uniformly random vertex in $W(v_{t-1}, t)$. We say a path (v_0, v_1, \dots, v_T) is generated by the random walk if $v_t \in W(v_{t-1}, t)$ for all $t \in [T]$. Denote by $p(u, t_1, v, t_2)$ the probability that the random walk is at v after step t_2 under the condition that the walk is at u after step t_1 . Let $p_t = \max_{u,v,t_1,t_2: t_2-t_1=t} p(u, t_1, v, t_2)$. For $(u, u') \in E$, let $q(u, u', t_1, v, t_2)$ be the probability that the walk is at v after step t_2 , under the conditions that 1) the walk is at u after step t_1 , and 2) the walk does not go to u' at step $t_1 + 1$. The following lemma on the relation of the two probabilities is obvious.

Lemma 8 If $|W(u, t_1 + 1)| > 1$, then $q(u, u', t_1, v, t_2) \leq 2p(u, t_1, v, t_2)$.

Proof By considering the two cases of the step $t_1 + 1$ (going to u' or not), we have

$$p(u, t_1, v, t_2) = \frac{1}{|W(u, t_1 + 1)|} p(u', t_1 + 1, v, t_2) + \left(1 - \frac{1}{|W(u, t_1 + 1)|}\right) q(u, u', t_1, v, t_2). \quad (14)$$

Thus

$$q(u, u', t_1, v, t_2) \leq p(u, t_1, v, t_2) / \left(1 - \frac{1}{|W(u, t_1 + 1)|}\right) \leq 2p(u, t_1, v, t_2). \quad (15)$$

□

Theorem 9 Suppose G contains $G^w \times G^c$ as a subgraph, and L is the length of the longest self-avoiding path in G^c . Let $T = \lfloor L/2 \rfloor$, then for the random walk (G^w, v_0^w, W) on G^w , we have

$$RLS(G) = \Omega\left(\frac{T}{\sum_{t=1}^T p_t}\right), \quad QLS(G) = \Omega\left(\frac{T}{\sum_{t=1}^T \sqrt{p_t}}\right). \quad (16)$$

Proof Without loss of generality, we assume $G = G^w \times G^c$, as Local Search on a subgraph is no harder than Local Search on the original graph. We shall construct a random walk on G by the random walk (G^w, v_0^w, W) on G^w and a simple one-way walk on G^c . Starting from some fixed vertex in G , the walk is proceeded by one step of walk in G^w followed by two steps of walk in G^c . (We perform *two* steps of walk in G^c mainly for some technical reasons, and this is where the factor of 2 in definition $T = \lfloor L/2 \rfloor$ comes from.) Precisely, fix a self-avoiding path $(z_{0,0}^c, z_{1,0}^c, z_{1,1}^c, z_{2,1}^c, z_{2,2}^c, \dots, z_{T,T-1}^c, z_{T,T}^c)$ of length $2T$ in G^c . Let the set P contain all the paths $X = (x_0^w \otimes z_{0,0}^c, x_1^w \otimes z_{0,0}^c, x_1^w \otimes z_{1,0}^c, x_1^w \otimes z_{1,1}^c, \dots, x_T^w \otimes z_{T-1,T-1}^c, x_T^w \otimes z_{T,T-1}^c, x_T^w \otimes z_{T,T}^c)$ in G such that $x_0^w = v_0^w$ and $(x_0^w, x_1^w, \dots, x_T^w)$ is a path generated by the random walk (G^w, v_0^w, W) . Define a problem PATH_P : given a path $X \in P$, find the end point $x_T^w \otimes z_{T,T}^c$. To access X , we can ask whether $v \in \text{set}(X)$ for any vertex $v \in V$, and an oracle O will give us the Yes/No answer.⁵ The following claim says that the PATH_P problem is not much harder than Local Search problem.

Claim 1 $R_2(\text{PATH}_P) \leq 2RLS(G)$, $Q_2(\text{PATH}_P) \leq 2QLS(G)$.

Proof Suppose we have an Q -query randomized or quantum algorithm \mathcal{A} for Local Search, we shall give a $2Q$ corresponding algorithm \mathcal{B} for PATH_P . For any path $X \in P$, we define a function f_X essentially in the same way as Aaronson did in [2]: for each vertex $v \in G$, let

$$f_X(v) = \begin{cases} |v - x_0^w \otimes z_{0,0}^c|_G + 3T & \text{if } v \notin \text{set}(X) \\ 3(T - k) & \text{if } v = x_k^w \otimes z_{k,k}^c \\ 3(T - k) - 1 & \text{if } v = x_{k+1}^w \otimes z_{k,k}^c \neq x_k^w \otimes z_{k,k}^c \\ 3(T - k) - 2 & \text{if } v = x_{k+1}^w \otimes z_{k+1,k}^c \end{cases} \quad (17)$$

It is easy to verify that the only local minimum is $x_T^w \otimes z_{T,T}^c$.

Given an oracle O and an input X of the PATH problem, \mathcal{B} simulates \mathcal{A} to find the local minimum of f_X , which is also the end point of X . Whenever \mathcal{A} needs to make a query on v to get $f_X(v)$, \mathcal{B} asks O whether $v \in \text{set}(X)$. If $v \notin \text{set}(X)$, then $f_X(v) = |v - x_0^w \otimes z_{0,0}^c|_G + 3T$; otherwise, $v = x^w \otimes z_{k+1,k}^c$ or $v = x^w \otimes z_{k,k}^c$ for some $x^w \in V^w$ and k . Note that k is known for any given vertex v . So if $v = x^w \otimes z_{k+1,k}^c$, then $x^w = x_{k+1}^w$ and thus $f_X(v) = 3(T - k) - 2$. Now consider the case that $v = x^w \otimes z_{k,k}^c$. If $k = 0$, then let $f_X(v) = 3T$ if $v = x_0^w \otimes z_{0,0}^c$ and $f_X(v) = 3T - 1$ otherwise. If $k \geq 1$, then \mathcal{B} asks O whether $x^w \otimes z_{k,k-1}^c \in \text{set}(X)$. If yes, then $v = x_k^w \otimes z_{k,k}^c$ and thus $f_X(v) = 3(T - k)$; if no, then $v = x_{k+1}^w \otimes z_{k,k}^c \neq x_k^w \otimes z_{k,k}^c$ and thus $f_X(v) = 3(T - k) - 1$.

⁵Note that it is actually an oracle for the following function $g : \{0, 1\}^n \rightarrow \{0, 1\}$, with $g(x) = 1$ if and only if $x \in \text{set}(X)$. So strictly speaking, an input of PATH_P should be specified as $\text{set}(X)$ rather than X , because in general, it is possible that $X \neq Y$ but $\text{set}(X) = \text{set}(Y)$. For our problem, however, it is easy to check that for any $X, Y \in P$, it holds that $X = Y \Leftrightarrow \text{set}(X) = \text{set}(Y)$. Actually, if $X \neq Y$, suppose the first diverging place is k , i.e. $x_{k-1}^w = y_{k-1}^w$, but $x_k^w \neq y_k^w$. Then Y will never pass $x_k^w \otimes z_{k,k-1}^c$ because the clock immediately ticks and the time always advances forward. (Or more rigorously, the only point that Y passes through $z_{k,k-1}^c$ is $y_k^w \otimes z_{k,k-1}^c$. Since $y_k^w \neq x_k^w$, $x_k^w \otimes z_{k,k-1}^c \notin \text{set}(Y)$.)

Therefore, at most 2 queries on O can simulate one query on f_X , so we have a $2Q$ algorithm for PATH_P in both randomized and quantum cases. \square

(Continue the proof of Theorem 9) By the claim, it is sufficient to prove lower bounds for PATH_P . We define a relation R_P as follows.

$$R_P = \{(X, Y) : X \in P, Y \in P, X \text{ and } Y \text{ has different end points}\}. \quad (18)$$

For any pair $(X, Y) \in R_P$, where $X = (x_0^w \otimes z_{0,0}^c, x_1^w \otimes z_{0,0}^c, x_1^w \otimes z_{1,0}^c, x_1^w \otimes z_{1,1}^c, \dots, x_T^w \otimes z_{T-1,T-1}^c, x_T^w \otimes z_{T,T-1}^c, x_T^w \otimes z_{T,T}^c)$ and $Y = (y_0^w \otimes z_{0,0}^c, y_1^w \otimes z_{0,0}^c, y_1^w \otimes z_{1,0}^c, y_1^w \otimes z_{1,1}^c, \dots, y_T^w \otimes z_{T-1,T-1}^c, y_T^w \otimes z_{T,T-1}^c, y_T^w \otimes z_{T,T}^c)$, we write $X \wedge Y = k$ if $x_0^w = y_0^w, \dots, x_{k-1}^w = y_{k-1}^w$ but $x_k^w \neq y_k^w$. Intuitively, $X \wedge Y = k$ if k is the place that the paths X and Y diverge for the first time. Note that if $X \wedge Y = k$, then $x_k^w, y_k^w \in W(x_{k-1}^w, k)$ and thus $|W(x_{k-1}^w, k)| \geq 2$. By Lemma 8, this implies that $q(x_{k-1}^w, x_k^w, k - 1, v^w, j) \leq 2p_{j-k+1}$.

We choose the weight functions in Theorem 6 by letting

$$w(X, Y) = 1/|\{Y' \in P : Y' \wedge X = k\}| \quad (19)$$

$$= 1/|\{X' \in P : X' \wedge Y = k\}| \quad (20)$$

$$= 1/[(c_k - 1)c_{k+1} \dots c_T]. \quad (21)$$

To calculate $w_X = \sum_{Y' : (X, Y') \in R_P} w(X, Y')$, we group those Y' that diverge from X at the same place k' :

$$w_X = \sum_{k'=1}^T \sum_{\substack{Y' : (X, Y') \in R_P \\ X \wedge Y' = k'}} w(X, Y') \quad (22)$$

$$= \sum_{k'=1}^T \sum_{\substack{Y' : (X, Y') \in R_P \\ X \wedge Y' = k'}} \frac{1}{|\{Y' \in P : Y' \wedge X = k'\}|} \quad (23)$$

$$= \sum_{k'=1}^T \Pr_{Y'}[(X, Y') \in R_P | Y' \wedge X = k'] \quad (24)$$

$$= \sum_{k'=1}^T \Pr_{Y'}[(y')_T^w \neq x_T^w | Y' \wedge X = k'] \quad (25)$$

Here Equality (24) holds because all paths diverging from X firstly at k' have the same probability $1/[(c_{k'} - 1)c_{k'+1} \dots c_T]$. Also note that the probability in the last equality is nothing but $1 - q(x_{k'-1}^w, x_{k'}^w, k' - 1, x_T^w, T)$, which is at least $1 - 2p_{T-k'+1}$. So we have

$$w_X \geq T - 2 \sum_{k'=1}^T p_{T-k'+1} = T - 2 \sum_{t=1}^T p_t. \quad (26)$$

And similarly, we have $w_Y \geq T - 2 \sum_{t=1}^T p_t$ too.

Now we define $u(X, Y, i)$ and $v(X, Y, i)$, where i is a point $x_{j+r}^w \otimes z_{j+s,j}^c \in \text{set}(X) - \text{set}(Y)$ or $y_{j+r}^w \otimes z_{j+s,j}^c \in \text{set}(Y) - \text{set}(X)$. Here $(r, s) \in \{(0, 0), (1, 0), (1, 1)\}$, and $0 \leq j \leq j+r \leq T$. Let

$$u(X, Y, x_{j+r}^w \otimes z_{j+s,j}^c) = a_{k,j,r,s} w(X, Y), \quad u(X, Y, y_{j+r}^w \otimes z_{j+s,j}^c) = b_{k,j,r,s} w(X, Y), \quad (27)$$

$$v(X, Y, x_{j+r}^w \otimes z_{j+s,j}^c) = b_{k,j,r,s} w(X, Y), \quad v(X, Y, y_{j+r}^w \otimes z_{j+s,j}^c) = a_{k,j,r,s} w(X, Y). \quad (28)$$

where $a_{k,j,r,s}$ and $b_{k,j,r,s}$ will be given later (satisfying $a_{k,j,r,s} b_{k,j,r,s} = 1$, which makes u, v, w really a weight scheme). We shall calculate $u_{X,i}$ and $v_{Y,i}$ for $i = x_{j+r}^w \otimes z_{j+s,j}^c \in \text{set}(X) - \text{set}(Y)$; the

other case $i = y_{j+r}^w \otimes z_{j+s,j}^c$ is just symmetric. Note that if $x_{j+r}^w \otimes z_{j+s,j}^c \notin \text{set}(Y')$ and $X \wedge Y' = k'$, then $k' \leq j + r$.

$$u_{X, x_{j+r}^w \otimes z_{j+s,j}^c} = \sum_{k'=1}^{j+r} \sum_{\substack{Y': (X, Y') \in R_P, X \wedge Y' = k' \\ x_{j+r}^w \otimes z_{j+s,j}^c \notin \text{set}(Y')}} a_{k', j, r, s} w(X, Y') \quad (29)$$

$$\leq \sum_{k'=1}^{j+r} \sum_{Y': X \wedge Y' = k'} a_{k', j, r, s} w(X, Y') \quad (30)$$

$$= \sum_{k'=1}^{j+r} a_{k', j, r, s} \quad (31)$$

The computation for $v_{Y, x_{j+r}^w \otimes z_{j+s,j}^c}$ is a little more complicated. By definition,

$$v_{Y, x_{j+r}^w \otimes z_{j+s,j}^c} = \sum_{k'=1}^{j+r} \sum_{\substack{X': (X', Y) \in R_P, X' \wedge Y = k', \\ x_{j+r}^w \otimes z_{j+s,j}^c \in \text{set}(X')}} b_{k', j, r, s} w(X', Y) \quad (32)$$

$$\leq \sum_{k'=1}^{j+r} \sum_{\substack{X': X' \wedge Y = k', \\ x_{j+r}^w \otimes z_{j+s,j}^c \in \text{set}(X')}} b_{k', j, r, s} w(X', Y) \quad (33)$$

$$= \sum_{k'=1}^{j+r} b_{k', j, r, s} \mathbf{Pr}_{X'}[x_{j+r}^w \otimes z_{j+s,j}^c \in \text{set}(X') | X' \wedge Y = k'] \quad (34)$$

We can see that by adding the clock, the passing probability $\mathbf{Pr}_{X'}[x_{j+r}^w \otimes z_{j+s,j}^c \in \text{set}(X') | X' \wedge Y = k']$ is roughly the hitting probability $q(y_{k'-1}^w, y_{k'}^w, k' - 1, x_{j+r}^w, j) + q(y_{k'-1}^w, y_{k'}^w, k' - 1, x_{j+r}^w, j + 1)$ except for some corner cases. To be more precise, define

$$\text{Bound}_{k', j, r, s} = 2p_{j-k'+2} \cdot \lambda[s = 1 \text{ OR } j < T] + 2p_{j-k'+1} \cdot \lambda[s = 0 \text{ AND } (k' \leq j \text{ OR } r = 0)] \quad (35)$$

where the Boolean function $\lambda[\phi] = 1$ if ϕ is true and 0 otherwise. Then

Claim 2 $\mathbf{Pr}_{X'}[x_{j+r}^w \otimes z_{j+s,j}^c \in \text{set}(X') | X' \wedge Y = k'] \leq \text{Bound}_{k', j, r, s}$.

Proof We study the probability $\mathbf{Pr}_{X'}[x_{j+r}^w \otimes z_{j+s,j}^c \in \text{set}(X') | X' \wedge Y = k']$ case by case. If $s = 1$, then $r = 1$, and $x_{j+1}^w \otimes z_{j+1,j}^c \in \text{set}(X')$ if and only if $x_{j+1}^w = (x')_{j+1}^w$. So

$$\mathbf{Pr}_{X'}[x_{j+r}^w \otimes z_{j+s,j}^c \in \text{set}(X') | X' \wedge Y = k'] = q(y_{k'-1}^w, y_{k'}^w, k' - 1, x_{j+1}^w, j + 1) \leq 2p_{j-k'+2} \quad (36)$$

by Lemma 8. If $s = 0$, then $x_{j+r}^w \otimes z_{j,j}^c \in \text{set}(X')$ if and only if " $x_{j+r}^w = (x')_j^w$ or $x_{j+r}^w = (x')_{j+1}^w$ ". Also note that

$$\mathbf{Pr}_{X'}[x_{j+r}^w = (x')_j^w | X' \wedge Y = k'] = q(y_{k'-1}^w, y_{k'}^w, k' - 1, x_{j+r}^w, j) \quad (37)$$

unless $k' = j + 1$ and $r = 1$, in which case $\mathbf{Pr}_{X'}[x_{j+r}^w = (x')_j^w | X' \wedge Y = k'] = 0$ because $x_{j+1}^w \otimes z_{j,j}^c \notin \text{set}(Y)$ but $(x')_j^w \otimes z_{j,j}^c = y_j^w \otimes z_{j,j}^c \in \text{set}(Y)$. The other probability

$$\mathbf{Pr}_{X'}[x_{j+r}^w = (x')_{j+1}^w | X' \wedge Y = k'] = \begin{cases} q(y_{k'-1}^w, y_{k'}^w, k' - 1, x_{j+r}^w, j + 1) & \text{if } j \leq T - 1 \\ 0 & \text{if } j = T \end{cases} \quad (38)$$

Putting all cases together, we get the desired result. \square

(Continue the proof of Theorem 9) The claim implies that

$$v_{Y, x_{j+r}^w \otimes z_{j+s,j}^c} \leq \sum_{k'=1}^{j+r} b_{k', j, r, s} \text{Bound}_{k', j, r, s}. \quad (39)$$

The symmetric case of $u(X, Y, i)$ and $v(X, Y, i)$ where i is a point $y_{j+r}^w \otimes z_{j+s,j}^c \in \text{set}(Y) - \text{set}(X)$ can be dealt with in the same way, yielding $u_{X, y_{j+r}^w \otimes z_{j+s,j}^c} \leq \sum_{k'=1}^{j+r} b_{k',j,r,s} \text{Bound}_{k',j,r,s}$ and $v_{Y, y_{j+r}^w \otimes z_{j+s,j}^c} \leq \sum_{k'=1}^{j+r} a_{k',j,r,s}$.

By the definition of $\text{Bound}_{k',j,r,s}$, it holds for any (j, r, s) that

$$\sum_{k'=1}^{j+r} \text{Bound}_{k',j,r,s} \leq 4 \sum_{t=1}^T p_t \quad \text{and} \quad \sum_{k'=1}^{j+r} \sqrt{\text{Bound}_{k',j,r,s}} \leq 4 \sum_{t=1}^T \sqrt{p_t}. \quad (40)$$

Now for the randomized lower bound, $a_{k',j,r,s} = b_{k',j,r,s} = 1$.

$$RLS(G) = \Omega \left(\min_{j,r,s} \max \left\{ \frac{T - 2 \sum_{t=1}^T p_t}{j+r}, \frac{T - 2 \sum_{t=1}^T p_t}{\sum_{k'=1}^{j+r} \text{Bound}_{k',j,r,s}} \right\} \right) = \Omega \left(\frac{T}{\sum_{t=1}^T p_t} \right). \quad (41)$$

For the quantum lower bound, pick $a_{k',j,r,s} = \sqrt{\text{Bound}_{k',j,r,s}}$, and $b_{k',j,r,s} = 1/\sqrt{\text{Bound}_{k',j,r,s}}$. Then

$$QLS(G) = \Omega \left(\min_{j,r,s} \sqrt{\frac{(T - 2 \sum_{t=1}^T p_t)(T - 2 \sum_{t=1}^T p_t)}{(\sum_{k'=1}^{j+r} \sqrt{\text{Bound}_{k',j,r,s}})(\sum_{k'=1}^{j+r} \sqrt{\text{Bound}_{k',j,r,s}})}} \right) = \Omega \left(\frac{T}{\sum_{t=1}^T \sqrt{p_t}} \right) \quad (42)$$

This completes the proof of Theorem 9. \square

4 Applications to the two special graphs

In this section, we will apply Theorem 9 to the two special graphs. Note that in both cases, the probability p_t is not easy to upper bound. Also note that we need not only to pick the random walk, but also the way to decomposed the graph.

4.1 Lower bounds for Local Search on the Boolean Hypercube

To apply Theorem 9 to $\{0, 1\}^n$, we decompose the whole graph into the two parts $\{0, 1\}^m$ and $\{0, 1\}^{n-m}$, where m is to be decided later (and to be taken different values for randomized and quantum lower bounds). Pick the random walk $(\{0, 1\}^m, v_0^w, W)$, where $v_0^w = 0^m \in \{0, 1\}^m$ and $W(x, t) = \{x^{(i)} : i \in \{0, \dots, m-1\}\}$ for each vertex $x = x_0 \dots x_{m-1} \in \{0, 1\}^m$ and each $t \in \mathbb{N}$. Finally, note that the longest self-avoiding path of the graph $\{0, 1\}^{n-m}$ is a Hamilton path with length $L = 2^{n-m} - 1$.

The following bounds on p_t are rather loose for $10 < t \leq m^2$ but sufficient for our purpose. The proof of the lemma uses some techniques in generating functions and Fourier analysis.

Lemma 10 *For any $t \in \mathbb{N}$, we have*

$$p_t = \begin{cases} O(m^{-\lceil t/2 \rceil}) & \text{if } t \leq 10 \\ O(m^{-5}) & \text{if } 10 < t \leq m^2 \\ O(2^{-m}) & \text{if } t > m^2 \end{cases} \quad (43)$$

Proof Consider that we put t balls randomly into m bins one by one. The j -th ball goes into the i_j -th bin. Denote by n_i the total number of balls in the i -th bin. We write $n_i \equiv b_i$ if $b_i = n_i \bmod 2$. We say that (i_1, \dots, i_t) generates the parity sequence (b_1, \dots, b_m) , or simply (i_1, \dots, i_t) generates (b_1, \dots, b_m) , if $n_i \equiv b_i$ for all $i \in [m]$. For $b_1 \dots b_m \in \{0, 1\}^m$, denote by $p^{(t)}[b_1, \dots, b_m]$ the probability that $n_i \equiv b_i, \forall i \in [m]$. Let $p^{(t)} = \max_{b_1, \dots, b_m} p^{(t)}[b_1, \dots, b_m]$. It is easy to see that $p^{(t)} = p_t$ in Lemma 10, so it is enough to prove the same bounds in Lemma 10 for $p^{(t)}$.

We start with several simple observations. First, we assume that t and $\sum_{i=1}^m b_i$ have the same parity, because otherwise the probability is 0 and the lemma holds trivially. Second, by the symmetry, any permutation of b_1, \dots, b_m does not change $p^{(t)}[(b_1, \dots, b_m)]$. Third, $p^{(t)}[(b_1, \dots, b_m)]$ decreases if we replace two 1's in b_1, \dots, b_m by two 0's. Precisely, if we have two b_i 's being 1, say $b_1 = b_2 = 1$, then $p^{(t)}[(b_1, \dots, b_m)] < p^{(t)}[(0, 0, b_3, \dots, b_m)]$. In fact, note that

$$p^{(t)}[(b_1, \dots, b_m)] = \frac{1}{m^t} \sum_{\substack{n_1 + \dots + n_m = t \\ n_i \equiv b_i, i \in [m]}} \frac{t!}{n_1! \dots n_m!} \quad (44)$$

$$= \frac{1}{m^t} \sum_{\substack{n_3 + \dots + n_m \leq t \\ n_i \equiv b_i, i=3, \dots, m}} \left(\frac{t!}{(n_1 + n_2)! n_3! \dots n_m!} \sum_{\substack{n_1 + n_2 = t - n_3 - \dots - n_m \\ n_i \equiv b_i, i=1,2}} \frac{(n_1 + n_2)!}{n_1! n_2!} \right) \quad (45)$$

where as usual, let $0! = 1$. If $n_3 + \dots + n_m < t$, then

$$\sum_{\substack{n_1 + n_2 = t - n_3 - \dots - n_m \\ n_i \equiv 1, i=1,2}} \frac{(n_1 + n_2)!}{n_1! n_2!} = \sum_{\substack{n_1 + n_2 = t - n_3 - \dots - n_m \\ n_i \equiv 0, i=1,2}} \frac{(n_1 + n_2)!}{n_1! n_2!} \quad (46)$$

If $n_3 + \dots + n_m = t$, then the only possible (n_1, n_2) is $(0, 0)$, so

$$\sum_{\substack{n_1 + n_2 = t - n_3 - \dots - n_m \\ n_i \equiv 1, i=1,2}} \frac{(n_1 + n_2)!}{n_1! n_2!} = 0, \quad \sum_{\substack{n_1 + n_2 = t - n_3 - \dots - n_m \\ n_i \equiv 0, i=1,2}} \frac{(n_1 + n_2)!}{n_1! n_2!} = 1. \quad (47)$$

Thus $p^{(t)}[(1, 1, b_3, \dots, b_m)] < p^{(t)}[(0, 0, b_3, \dots, b_m)]$.

By the observations, it is sufficient to prove the lemma for the case $p^{(t)}[(0, \dots, 0)]$ if t is even, and for the case $p^{(t)}[(1, 0, \dots, 0)]$ if t is odd. Note that if t is even, then

$$p^{(t)}[(0, \dots, 0)] = \sum_{i=1}^m \mathbf{Pr}[i_1 = i] \mathbf{Pr}[(i_2, \dots, i_t) \text{ generates } (e_i)] \quad (48)$$

where e_i is the m -long vector with only coordinate i being 1 and all other coordinates being 0. By the symmetry, $p^{(t-1)}[e_1] = \dots = p^{(t-1)}[e_m]$, thus $p^{(t)}[(0, \dots, 0)] = p^{(t-1)}[e_1] = p^{(t-1)}[1, 0, \dots, 0]$. Therefore, it is enough to show the lemma for even t .

We now express $p^{(t)}[0, \dots, 0]$ in two ways. One is to prove the first case ($t \leq 10$) in the lemma, and the other is for the second case ($10 < t \leq m^2$) and the third case ($t > m^2$) in the lemma.

To avoid confusion, we write the number m of bins explicitly as subscript: $p_m^{(t)}[b_1, \dots, b_m]$. We consider which bin(s) the first two balls is put into.

$$p_m^{(t)}[0, \dots, 0] = \mathbf{Pr}[i_1 = i_2] p_m^{(t-2)}[0, \dots, 0] + \mathbf{Pr}[i_1 \neq i_2] p_m^{(t-2)}[1, 1, 0, \dots, 0] \quad (49)$$

$$= \frac{1}{m} p_m^{(t-2)}[0, \dots, 0] + \frac{m-1}{m} p_m^{(t-2)}[1, 1, 0, \dots, 0] \quad (50)$$

To compute $p_m^{(t-2)}[1, 1, 0, \dots, 0]$, we consider to put $(t-2)$ balls in m bins. By the analysis of the third observations above, we know that

$$p_m^{(t-2)}[0, \dots, 0] - p_m^{(t-2)}[1, 1, 0, \dots, 0] \quad (51)$$

$$= \mathbf{Pr}[n_1 = n_2 = 0, n_3 \equiv 0, \dots, n_m \equiv 0] \quad (52)$$

$$= \mathbf{Pr}[n_1 = n_2 = 0] \mathbf{Pr}[n_3 \equiv 0, \dots, n_m \equiv 0 | n_1 = n_2 = 0] \quad (53)$$

$$= \left(\frac{m-2}{m} \right)^{t-2} p_{m-2}^{(t-2)}[0, \dots, 0] \quad (54)$$

Therefore,

$$p_m^{(t)}[0, \dots, 0] = \frac{1}{m} p_m^{(t-2)}[0, \dots, 0] - \frac{m-1}{m} \left(\frac{m-2}{m} \right)^{t-2} p_{m-2}^{(t-2)}[0, \dots, 0] \quad (55)$$

Now using the above recursive formula and the base case $p_m^{(2)}[0, \dots, 0] = 1/m$, it is easy (but tedious) to prove by calculations that $p_m^{(t)}[0, \dots, 0] = ((t-1)!!/m^{\frac{t}{2}})(1 - o(1))$ for even $t \leq 10$. This proves the first case in the lemma.

For the rest two cases, we shall use generating function and some technique inspired by Fourier analysis. Consider the generating function

$$(x_1 + \dots + x_m)^t = \sum_{n_1 + \dots + n_m = t} \binom{t}{n_1, \dots, n_m} x_1^{n_1} \dots x_m^{n_m}. \quad (56)$$

If $x_i \in \{-1, 1\}$, then $(x_1 + \dots + x_m)^t = \sum_{n_1 + \dots + n_m = t} \binom{t}{n_1, \dots, n_m} (-1)^{|\{i: x_i = -1, n_i \equiv 1\}|}$. We sum it over all $x_1 \dots x_m \in \{-1, 1\}^m$. Note that for those (n_1, \dots, n_m) that has some $n_{i_0} \equiv 1$, it holds due to the cancelation that $\sum_{x_1, \dots, x_m \in \{-1, 1\}} (-1)^{|\{i: x_i = -1, n_i \equiv 1\}|} = 0$. On the other hand, if all n_i 's are even, then $\sum_{x_1, \dots, x_m \in \{-1, 1\}} (-1)^{|\{i: x_i = -1, n_i \equiv 1\}|} = 2^m$. Thus we have

$$\sum_{x_1, \dots, x_m \in \{-1, 1\}} (x_1 + \dots + x_m)^t = 2^m \sum_{\substack{n_1 + \dots + n_m = t \\ n_i \equiv 0, i \in [m]}} \binom{t}{n_1, \dots, n_m}. \quad (57)$$

And therefore,

$$p^{(t)}[0, \dots, 0] = \frac{1}{m^t} \sum_{\substack{n_1 + \dots + n_m = t \\ n_i \equiv 0, i \in [m]}} \binom{t}{n_1, \dots, n_m} \quad (58)$$

$$= \frac{1}{2^m m^t} \sum_{x_1, \dots, x_m \in \{-1, 1\}} (x_1 + \dots + x_m)^t \quad (59)$$

$$= \frac{1}{2^m m^t} \sum_{i=0}^m \binom{m}{i} (m - 2i)^t \quad (60)$$

$$= \frac{1}{2^m} \sum_{i=0}^m \binom{m}{i} \left(1 - \frac{2i}{m}\right)^t. \quad (61)$$

Note that t is even, so $p^{(t)}[0, \dots, 0]$ decreases if t increases by 2, and this proves the second case of the lemma with the help of the first case. And if $t > m^2/2$, then

$$p^{(t)}[0, \dots, 0] \leq \frac{1}{2^m} \left(2 + \left(1 - \frac{2}{m}\right)^t \sum_{i=1}^{m-1} \binom{m}{i}\right) < 2/2^m + e^{-m} = O(1/2^m) \quad (62)$$

This proves the third case of the lemma. \square

Now it is very easy to prove Theorem 2 using this lemma. For the randomized lower bound, let $m = \lfloor (n + \log_2 n)/2 \rfloor$, then $T = \Theta(2^{n/2}/n^{1/2})$ and $\sum_{t=1}^T p_t = O(1/n)$. Thus $RLS(\{0, 1\}^n) = \Omega(\sqrt{n} 2^{n/2})$. For the quantum lower bound, let $m = \lfloor (2n + \log_2 n)/3 \rfloor$, then $T = \Theta(2^{n/3}/n^{1/3})$ and $\sum_{t=1}^T \sqrt{p_t} = O(1/\sqrt{n})$. Thus $QLS(\{0, 1\}^n) = \Omega(2^{n/3} n^{1/6})$.

4.2 Lower bounds for Local Search on the constant dimensional grid

In this section we shall first prove a lower bound weaker than Theorem 3 in Section 4.2.1, and then improve it to Theorem 3 in Section 4.2.2 and Section 4.2.3.

4.2.1 A weaker family of lower bounds

To simplify notations, we let $n = N^{1/d}$. As in Section 4.1, we decompose the grid into two parts, $[n]^m$ and $[n]^{d-m}$. For each vertex $x = x_0 \dots x_{m-1} \in [n]^m$ and each $i \in \{0, \dots, m-1\}$, define

$$x^{(i), -} = x_0 \dots x_{i-1} \max\{x_i - 1, 1\} x_{i+1} \dots x_{m-1}, \quad (63)$$

$$x^{(i), +} = x_0 \dots x_{i-1} \min\{x_i + 1, n\} x_{i+1} \dots x_{m-1}. \quad (64)$$

We perform the random walk $([n]^m, v_0^w, W)$ where $v_0^w = 00\dots 0 \in [n]^m$ and

$$W(x, t) = \{x^{((t-1) \bmod m), +}, x^{((t-1) \bmod m), -}\}. \quad (65)$$

To analyze the probability p_t in Theorem 9, we first consider the following simpler “line walk”. Suppose a particle is initially put at point $i \in \{1, \dots, n\}$, and in each step the particle moves either to $\max\{1, i-1\}$ or to $\min\{n, i+1\}$, each with probability $1/2$. Let $p_{ij}^{(t)}$ denote the probability that the particle starting from point i stops at point j after exact t steps of the walk. For $t \geq 1$, the following proposition gives a very good (actually tight) estimate on $\max_{ij} p_{ij}^{(t)}$.

Proposition 11 *For any $t \geq 1$,*

$$\max_{i,j} p_{ij}^{(t)} = \begin{cases} O(1/\sqrt{t}) & \text{if } t \leq n^2 \\ O(1/n) & \text{if } t > n^2 \end{cases} \quad (66)$$

Before the formal proof, let us briefly discuss the main difficulty and the idea to get around it. First note that since we care about the whole mixing process (*i.e.* before and after mixing), the standard eigenvalue gap does not immediately apply. Second, if there are not the two barriers (1 and n) then $p_{ij}^{(t)}$ is very easy to calculate: $p_{ij}^{(t)} = \binom{t}{t/2 + (j-i)/2}$ if $j-i$ and t have the same parity, and 0 otherwise. However, since we now have the two barriers, it is hard to count the number of paths from i to j after exactly t steps. Fortunately, there is a basic *reflecting rule* as follows.

reflecting rule: In the line walk without barrier, the number of paths from $i > 0$ to $j > 0$ in exactly t steps touching or crossing the point 0 is equal to the number of paths from $-i$ to j in exactly t steps.

The proof of this rule is very easy. Suppose a random path touches the point 0 at t for the first time, then do a reflection of the first t steps of the path with respect to point 0. See Figure 1 for an illustration. It is not hard to see that this gives a 1-1 correspondence between the following two sets: 1) the set of paths from i to j after exactly t steps touching or crossing the point 0, and 2) the set of paths from $-i$ to j .

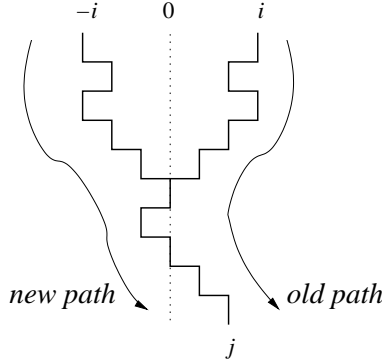


Figure 1: The proof of the reflecting rule.

Now let us consider the barrier setting. Note that a path may try to cross the two barriers in some pattern, for example, try to cross the left barrier (*i.e.* point 1) for a times and then try to cross the right barrier (*i.e.* point n) for b times. Imagine that we now remove the two barriers, then the path will touch (from right) but not cross the point $1-a$ and will touch (from left) but not cross the point $n+b-a$. To use the reflecting rule, we just need to further note the following simple fact:

$$\begin{aligned} & \{\text{paths touching but not crossing the point } 1-a\} \\ = & \{\text{paths touching or crossing the point } 1-a\} - \{\text{paths touching or crossing the point } -a\}. \end{aligned}$$

Following this idea, we will construct a series of 1-1 correspondences to reduce the problem step by step to the no-barrier case. The precise proof is as follows.

Proof We consider two settings. One is the line walk on n points $0, \dots, n-1$ with the two barriers 0 and $n-1$ ⁶. Another is the same except that the barriers are removed, and we have infinite points in a line. For each t -bit binary string $x = x_1 \dots x_t$, we use P_i^x and Q_i^x to denote the two paths that starting at i and walk according to x in the two settings. Precisely, at step s , Q_i^x goes left if $x_s = 0$ and goes right if $x_s = 1$. P_i^x goes in the same way except that it will stand still if the point is currently at left (or right) end and it still wants to go left (or right). If the end point of P_i^x is j , then we write $i \rightarrow_t^{P,x} j$. Let $X_{ij}^{(t),P}$ be the set of $x \in \{0,1\}^t$ s.t. $i \rightarrow_t^{P,x} j$, and put $n_{ij}^{(t),P} = |X_{ij}^{(t),P}|$. Then by definition, $p_{ij}^{(t)} = n_{ij}^{(t),P}/2^t$. The notations $i \rightarrow_t^{Q,x} j$, $X_{ij}^{(t),Q}$ and $n_{ij}^{(t),Q}$ are similarly defined, with the corresponding P changed to Q . Note that $n_{ij}^{(t),Q} = \binom{t/2+(j-i)/2}{t/2+(j-i)/2}$ if $j-i$ and t have the same parity, and 0 otherwise. We now want to upper bound $n_{ij}^{(t),P}$ in terms of $n_{ij}^{(t),Q}$.

For a path P_i^x , if at some step it is at point 0 and wants to go left, we say it *attempts to pass the left barrier*. Similarly for the right barrier. We say a path is in the $\{a_s, b_s\}_{s=1}^l$ category if it first attempts to pass the left barrier for a_1 times, and then attempts to pass the right barrier for b_1 times, and so on. We call each round a stage s , which begins at the time that P_i^x attempts to pass the left barrier for the $(a_1 + \dots + a_{s-1} + 1)$ -th time, and ends right before the time that P_i^x attempts to pass the left barrier for the $(a_1 + \dots + a_s + 1)$ -th time. We also split each stage s into two halves, cutting at the time right before the path attempts to pass the right barrier for the $(b_1 + \dots + b_{s-1} + 1)$ -th time. Note that a_1 may be 0, which means that the path first attempts to pass the right barrier. Also b_l may be 0, which means the the last barrier the path attempts to pass is the left one. But all other a_i, b_i 's are positive. Also note that in the case of $l = 0$, the path never attempts to pass either barrier. Now for any fixed $l > 0$, we consider those categories with $a_1 > 0$ and $b_l > 0$. Other cases can handled similarly. Partition $X_{ij}^{(t),P}$ as

$$X_{ij}^{(t),P} = \bigcup_{l, \{a_s, b_s\}_{s=1}^l} X_{ij}^{(t),P}[\{a_s, b_s\}_{s=1}^l] \quad (67)$$

where $X_{ij}^{(t),P}[\{a_s, b_s\}_{s=1}^l]$ contains those $x \in \{0,1\}^t$ s.t. P_i^x is in the category $\{a_s, b_s\}_{s=1}^l$. Put $n_{ij}^{(t),P}[\{a_s, b_s\}_{s=1}^l] = |X_{ij}^{(t),P}[\{a_s, b_s\}_{s=1}^l]|$, thus $n_{ij}^{(t),P} = \sum_l \sum_{\{a_s, b_s\}_{s=1}^l} n_{ij}^{(t),P}[\{a_s, b_s\}_{s=1}^l]$.

Now consider the corresponding paths in $X_{ij}^{(t),Q}$. The following observation relates P_i^x and Q_i^x .

Observation 1 For each $x \in X_{ij}^{(t),P}[\{a_s, b_s\}_{s=1}^l]$, the following two properties hold for any s .

1. In the first half of stage s , the path Q_i^x touches (from right) but does not cross the point $\alpha_s = \sum_{r=1}^{s-1} (b_r - a_r) - a_s$.
2. In the second half of stage s , the path Q_i^x touches (from left) but does not cross the point $\beta_s = n - 1 + \sum_{r=1}^s (b_r - a_r)$.
3. The path Q_i^x ends at $\gamma = j + \sum_{s=1}^l (b_s - a_s)$.

We let $Y_{i\gamma}^{(t),Q}[\{\alpha_s, \beta_s\}_{s=1}^l]$ contain those $x \in \{0,1\}^t$ satisfying the three conditions in the above observation, and denote by $m_{i\gamma}^{(t),Q}[\{\alpha_s, \beta_s\}_{s=1}^l]$ the size of the set $Y_{i\gamma}^{(t),Q}[\{\alpha_s, \beta_s\}_{s=1}^l]$. Thus the observation says $X_{ij}^{(t),P}[\{a_s, b_s\}_{s=1}^l] \subseteq Y_{i\gamma}^{(t),Q}[\{\alpha_s, \beta_s\}_{s=1}^l]$, and therefore we have $n_{ij}^{(t),P}[\{a_s, b_s\}_{s=1}^l] \leq m_{i\gamma}^{(t),Q}[\{\alpha_s, \beta_s\}_{s=1}^l]$. So it is enough to upper bound $m_{i\gamma}^{(t),Q}[\{\alpha_s, \beta_s\}_{s=1}^l]$.

Now for each $x \in Y_{i\gamma}^{(t),Q}[\{\alpha_s, \beta_s\}_{s=1}^l]$, if we change the condition 1 in state $s = 1$ by allowing the path to cross the point α_1 , and let $Z_{i\gamma}^{(t),Q}[\{\alpha_s, \beta_s\}_{s=1}^l]$ be the new set satisfying the new conditions, then $m_{i\gamma}^{(t),Q}[\{\alpha_s, \beta_s\}_{s=1}^l] = |Z_{i\gamma}^{(t),Q}[\{\alpha_s, \beta_s\}_{s=1}^l]| - |Z_{i\gamma}^{(t),Q}[\alpha_1 - 1, \beta_1, \{\alpha_s, \beta_s\}_{s=2}^l]|$. In other words, the set of paths touches (from right) but does not cross α_1 is the set of paths touches or crosses α_1 minus the set of paths touches or crosses $\alpha_1 - 1$.

⁶Here we let the n points be $0, \dots, n-1$ instead of $1, \dots, n$ just to make the later calculation cleaner.

Now we calculate $|Z_{i\gamma}^{(t),Q}[\{\alpha_s, \beta_s\}_{s=1}^l]|$ by the so-called reflection rule. Suppose the first time that Q_i^x touches α_1 is t_1 . We reflect the first t_1 part of the path Q_i^x with respect to the point α_1 . Precisely, let $y = (1 - x_1) \dots (1 - x_{t_1}) x_{t_1+1} \dots x_t$, then the paths Q_i^x and $Q_{2\alpha_1-i}^y$ merge at time t_1 . And it is easy to check that it is a 1-1 correspondence between $Z_{i\gamma}^{(t),Q}[\{\alpha_s, \beta_s\}_{s=1}^l]$ and $Y_{2\alpha_1-i,\gamma}^{(t),Q}[\beta_1, \{\alpha_s, \beta_s\}_{s=2}^l]$. Here $Y_{2\alpha_1-i,\gamma}^{(t),Q}[\beta_1, \{\alpha_s, \beta_s\}_{s=2}^l]$ is the set of paths starting at $2\alpha_1 - i$, satisfying (a) the condition 2 at the first stage, (b) both conditions 1 and 2 at the rest $l - 1$ stages, and (c) condition 3. So

$$|Z_{i\gamma}^{(t),Q}[\{\alpha_s, \beta_s\}_{s=1}^l]| = |Y_{2\alpha_1-i,\gamma}^{(t),Q}[\beta_1, \{\alpha_s, \beta_s\}_{s=2}^l]| = m_{2\alpha_1-i,\gamma}^{(t),Q}[\beta_1, \{\alpha_s, \beta_s\}_{s=2}^l] \quad (68)$$

$$= m_{-2a_1-i,\gamma}^{(t),Q}[\beta_1, \{\alpha_s, \beta_s\}_{s=2}^l] \quad (69)$$

$$= m_{-a_1-i,\gamma+a_1}^{(t),Q}[\beta_1 + a_1, \{\alpha_s + a_1, \beta_s + a_1\}_{s=2}^l] \quad (70)$$

where (69) is due to the fact that $\alpha_1 = -a_1$, and (70) is because that the number of the paths does not change if we move all the paths right by a_1 . Similarly, we have

$$|Z_{i\gamma}^{(t),Q}[\alpha_1 - 1, \beta_1, \{\alpha_s, \beta_s\}_{s=2}^l]| = m_{2\alpha_1-2-i,\gamma}^{(t),Q}[\beta_1, \{\alpha_s, \beta_s\}_{s=2}^l] \quad (71)$$

$$= m_{-a_1-2-i,\gamma+a_1}^{(t),Q}[\beta_1 + a_1, \{\alpha_s + a_1, \beta_s + a_1\}_{s=2}^l] \quad (72)$$

Therefore,

$$n_{ij}^{(t),P}[\{a_s, b_s\}_{s=1}^l] \leq m_{i\gamma}^{(t),Q}[\{\alpha_s, \beta_s\}_{s=1}^l] \quad (73)$$

$$= m_{-2a_1-i,\gamma}^{(t),Q}[\beta_1, \{\alpha_s, \beta_s\}_{s=2}^l] - m_{-2a_1-2-i,\gamma}^{(t),Q}[\beta_1, \{\alpha_s, \beta_s\}_{s=2}^l] \quad (74)$$

$$= m_{-a_1-i,\gamma+a_1}^{(t),Q}[\beta_1 + a_1, \{\alpha_s + a_1, \beta_s + a_1\}_{s=2}^l] \quad (75)$$

$$- m_{-a_1-2-i,\gamma+a_1}^{(t),Q}[\beta_1 + a_1, \{\alpha_s + a_1, \beta_s + a_1\}_{s=2}^l] \quad (76)$$

Note that $\alpha_s + a_1 = b_1 + \sum_{r=2}^{s-1} (b_r - a_r) - a_s$, $\beta_s + a_1 = n - 1 + b_1 + \sum_{r=2}^s (b_r - a_r)$ and $\gamma + a_1 = j + b_1 + \sum_{r=2}^s (b_r - a_r)$ are all functions of $(b_1, a_2, b_2, \dots, a_l, b_l)$, not of a_1 any more. Therefore,

$$\sum_{a_1, b_1, \dots, a_l, b_l > 0} n_{ij}^{(t),P}[\{a_s, b_s\}_{s=1}^l] \quad (77)$$

$$\leq \sum_{b_1, \dots, a_l, b_l > 0} \sum_{a_1 > 0} (m_{-a_1-i,\gamma+a_1}^{(t),Q}[\beta_1 + a_1, \{\alpha_s + a_1, \beta_s + a_1\}_{s=2}^l] \quad (78)$$

$$- m_{-a_1-2-i,\gamma+a_1}^{(t),Q}[\beta_1 + a_1, \{\alpha_s + a_1, \beta_s + a_1\}_{s=2}^l]) \quad (79)$$

$$= \sum_{b_1, \dots, a_l, b_l > 0} (m_{-1-i,\gamma+a_1}^{(t),Q}[\beta_1 + a_1, \{\alpha_s + a_1, \beta_s + a_1\}_{s=2}^l] \quad (80)$$

$$+ m_{-2-i,\gamma+a_1}^{(t),Q}[\beta_1 + a_1, \{\alpha_s + a_1, \beta_s + a_1\}_{s=2}^l]) \quad (81)$$

$$\leq \sum_{b_1, \dots, a_l, b_l > 0} 2 \max_{h=1,2} \{m_{-h-i,\gamma+a_1}^{(t),Q}[\beta_1 + a_1, \{\alpha_s + a_1, \beta_s + a_1\}_{s=2}^l]\} \quad (82)$$

Now using the similar methods, *i.e.* reflecting with respect to points $(n - 1 + b_1)$ and $(n + b_1)$, moving the paths left by b_1 , and finally collapsing the telescope, we can get

$$\sum_{b_1, \dots, a_l, b_l > 0} m_{-h-i,\gamma+a_1}^{(t),Q}[\beta_1 + a_1, \{\alpha_s + a_1, \beta_s + a_1\}_{s=2}^l] \quad (83)$$

$$\leq \sum_{a_2, b_2, \dots, a_l, b_l > 0} 2 \max_{k=1,2} \{m_{2n+i+h-k+1,\gamma+a_1-b_1}^{(t),Q}[\{\alpha_s + a_1 - b_1, \beta_s + a_1 - b_1\}_{s=2}^l]\} \quad (84)$$

and thus

$$\sum_{a_1, b_1, \dots, a_l, b_l > 0} n_{ij}^{(t), P} [\{a_s, b_s\}_{s=1}^l] \quad (85)$$

$$\leq \sum_{a_2, b_2, \dots, a_l, b_l > 0} 4 \max_{h=0,1,2} \{m_{2n+i+h, \gamma+a_1-b_1}^{(t), Q} [\{\alpha_s + a_1 - b_1, \beta_s + a_1 - b_1\}_{s=2}^l]\} \quad (86)$$

We continue this process, and finally we get

$$\sum_{a_1, b_1, \dots, a_l, b_l > 0} n_{ij}^{(t), P} [\{a_s, b_s\}_{s=1}^l] \leq 2^{2l} \max_{h=0,1,\dots,2l} n_{2ln+i+h, \gamma+\sum_{s=1}^l (a_s-b_s)}^{(t), Q} \quad (87)$$

$$= 2^{2l} \max_{h=0,1,\dots,2l} n_{2ln+i+h, j}^{(t), Q} \quad (88)$$

$$= 2^{2l} n_{2ln+i, j}^{(t), Q} \quad (89)$$

$$\leq 2^{2l} \binom{t}{\frac{t}{2} + \frac{j-i-2ln}{2}} \quad (90)$$

Thus

$$\sum_{l>0} \sum_{a_1, b_1, \dots, a_l, b_l > 0} n_{ij}^{(t), P} [\{a_s, b_s\}_{s=1}^l] \quad (91)$$

$$\leq \sum_{l \geq 0} 2^{2(l+1)} \binom{t}{\frac{t}{2} + ln} \quad (92)$$

$$= 4 \binom{t}{t/2} + \sum_{l \geq 1} 2^{2(l+1)} \binom{t}{t/2 + ln} \quad (93)$$

$$\leq 4 \binom{t}{t/2} + \frac{1}{n} \sum_{l \geq 1} 2^{2(l+1)} \left(\binom{t}{t/2 + ln} + \binom{t}{t/2 + ln - 1} + \dots + \binom{t}{t/2 + ln - n + 1} \right) \quad (94)$$

$$\leq 4 \binom{t}{t/2} + \frac{1}{n} \sum_{l \geq 1} 2^{2(l+1)} \left(\binom{t}{t} + \binom{t}{t-1} + \dots + \binom{t}{t/2 + ln - n + 1} \right) \quad (95)$$

$$\leq 4 \binom{t}{t/2} + \frac{1}{n} \sum_{l \geq 1} 2^{2(l+1)} 2^t e^{-\frac{2(l-1)^2 n^2}{3t}} \quad (96)$$

where $\binom{t}{t'} = 0$ if $t' > t$. Here the first two inequalities are by the monotonicity of binomial coefficients, and the last inequality is by Chernoff's Bound. Now if $t \leq n^2$, then $\sum_{l \geq 1} 2^{2(l+1)} e^{-\frac{2(l-1)^2 n^2}{3t}} \leq \sum_{l \geq 1} 2^{2(l+1)} e^{-\frac{2(l-1)^2}{3}} = O(1)$, so $\sum_{l>0} \sum_{a_1, b_1, \dots, a_l, b_l > 0} n_{ij}^{(t), P} [\{a_s, b_s\}_{s=1}^l] \leq O(\binom{t}{t/2} + 2^t/n) = O(2^t/\sqrt{t})$. For other categories of $a_1 = 0$ or $b_l = 0$, the same result can be proved similarly, and the $l = 0$ is easy since $n_{ij}^{(t), Q} = O(2^t/\sqrt{t})$. Putting all things together, we see that $p_{ij}^{(t)} = O(1/\sqrt{t})$ if $t \leq n^2$. The other part, i.e. $p_{ij}^{(t)} = O(1/n)$ when $t > n^2$, can be easily derived from this and the fact that $\max_{ij} p_{ij}^{(t)}$ decreases as t increases. This completes our proof. \square

Now we use Proposition 11 to prove the weaker lower bounds for grids. Since the random walk $([n]^m, v_0^w, W)$ is just a product of m line walks, it is not hard to see that the p_t in the random walk $([n]^m, v_0^w, W)$ satisfies

$$p_t = \begin{cases} O(1/\sqrt{t^m}) & \text{if } t \leq n^2, \\ O(1/n^m) & \text{if } t > n^2. \end{cases} \quad (97)$$

Now for the randomized lower bounds, when $d > 4$ we pick $m = \lceil d/2 \rceil > 2$ and we get

$$RLS([n]^d) = \Omega \left(\frac{n^{d-m}}{O(1) + n^{d-m}/n^m} \right) = \Omega(n^{\lceil d/2 \rceil}) = \begin{cases} \Omega(n^{\frac{d}{2}}) & \text{if } d \text{ is odd,} \\ \Omega(n^{\frac{d}{2} - \frac{1}{2}}) & \text{if } d \text{ is even.} \end{cases} \quad (98)$$

For $d = 4, 3, 2$, we let $m = 2, 2, 1$ respectively, and get $RLS([n]^4) = \Omega(n^2/(\log n + 1)) = \Omega(n^2/\log n)$, $RLS([n]^3) = \Omega(n/(\log n + 1/n)) = \Omega(n/\log n)$, and $RLS([n]^2) = \Omega(n/(\sqrt{n} + 1)) = \Omega(\sqrt{n})$.

For the quantum lower bounds, if $d > 6$, we let m be the integer closest to $2d/3$, thus $m > 4$. We get

$$QLS([n]^d) = \Omega\left(\frac{n^{d-m}}{O(1) + n^{d-m}/n^{m/2}}\right) = \begin{cases} \Omega(N^{\frac{1}{3}}) & \text{if } d = 3d' \\ \Omega(N^{\frac{1}{3} - \frac{1}{3d}}) & \text{if } d = 3d' + 1 \\ \Omega(N^{\frac{1}{3} - \frac{1}{6d}}) & \text{if } d = 3d' + 2 \end{cases} \quad (99)$$

For $d = 6$, let $m = 4$ and we have $QLS([n]^6) = \Omega(n^2/\log n)$. For $d = 5, 4, 3$, we let $m = d - 2$ and then $QLS([n]^d) = \Omega(n^2/(n^{2-(d-2)/2} + n^{2-(d-2)/2})) = \Omega(n^{d/2-1})$, which is $\Omega(n^{5/2}), \Omega(n^2), \Omega(n^{3/2})$, respectively. For $d = 2$, let $m = 1$ and $QLS([n]^2) = \Omega(\frac{n}{n^{3/4}}) = \Omega(n^{1/4})$.

4.2.2 Improvement

One weakness of the above proof is the integer constraint of the dimension m . We now show a way to get around the problem, allowing m to be any real number between 0 and $d - 1$. The idea is to partition the grid into many blocks, with different blocks representing different time slots, and the blocks are threaded into one very long block by many paths that are pairwise disjoint. Roughly speaking, we view $[n]^d$ as the product of d line graphs $[n]$. For each of the first $d - 1$ line graphs, we cut it into n^{1-r} parts evenly, each of size n^r . (Here $r = m/(d - 1)$). Then $[n]^{d-1}$ is partitioned into $n^{(d-1)(1-r)}$ smaller grids, all isomorphic to $[n^r]^{d-1}$. Putting the last dimension back, we have $n^{(d-1)(1-r)}$ blocks, all isomorphic to $[n^r]^{d-1} \times [n]$. Now the random walk will begin in the first block, and within each block, it is just one step of random walk in $[n^r]^{d-1}$ followed by two steps of one-way walk in the last dimension space $[n]$. When the walk runs out of the clock $[n]$, the walk will move to the next block via a particular block-changing path. All block-changing paths are carefully designed to be disjoint, and they “thread” all the blocks to form a $[n^r]^{d-1} \times [L]$ grid, where $L = (n - 2n^r)n^{(1-r)(d-1)}$. (L is not $n \cdot n^{(1-r)(d-1)}$ because we need $2n^r$ points for the block-changing paths.) Figure 2 is an illustration for the case of $d = 2$.

We now describe the partition and the walk precisely. For $x = x_0 \dots x_{d-1}$ in $[n]^d$, let $x^{(k)=l} = x_0 \dots x_{k-1} l x_{k+1} \dots x_{d-1}$, and $x^{(k)=(k)+i} = x_0 \dots x_{k-1} (x_k + i) x_{k+1} \dots x_{d-1}$, where i satisfies $x_k + i \in [n]$. Recall that $x^{(i),-} = x^{(i)=\max\{x_i-1, 1\}}$ and $x^{(i),+} = x^{(i)=\min\{x_i+1, n\}}$.

For any fixed constant $r \in (0, 1)$, let $\alpha = \lfloor n^r \rfloor$, $\beta = \lfloor n^{1-r} \rfloor$ and $n' = \alpha\beta$. Note that $n' \geq (n^r - 1)(n^{1-r} - 1) = n - o(n)$. We now consider the slightly smaller grid $[n']^d$. Let V_1 be the set $[n']^{d-1} = \{x_0 \dots x_{d-2} : x_i \in [n']\}$. We cut V_1 into β^{d-1} parts $\{x_0 \dots x_{d-2} : (k_i - 1)\alpha < x_i \leq k_i\alpha\}_{k_0 \dots k_{d-2} \in [\beta]^{d-1}}$, each of which is a small grid isomorphic to $[\alpha]^{d-1}$. We then refer to the set $\{x_0 \dots x_{d-2} x_{d-1} : (k_i - 1)\alpha < x_i \leq k_i\alpha, i = 0, \dots, d-2, \alpha < x_{d-1} \leq n' - \alpha\}$ as the “block (k_0, \dots, k_{d-2}) ”. Note that (k_0, \dots, k_{d-2}) can be also viewed as a point in grid $[\beta]^{d-1}$, and there is a Hamilton path $HamPath_{\beta, d-1}$ in $[\beta]^{d-1}$, as defined in Section 2. We call the block (k'_0, \dots, k'_{d-2}) the next block of the block (k_0, \dots, k_{d-2}) if (k'_0, \dots, k'_{d-2}) , viewed as the point in $[\beta]^{d-1}$, is the next point of (k_0, \dots, k_{d-2}) in $HamPath_{\beta, d-1}$. Note that by our definition of $HamPath_{\beta, d-1}$, we know that $\exists i \in \{0, \dots, d-2\}$ s.t. $k'_i \in \{k_i + 1, k_i - 1\}$ and for all other $j \neq i$, $k'_j = k_j$. That is, adjacent blocks have only one coordinate to be different, and this difference is 1. We call the the block (k_0, \dots, k_{d-2}) the last block if (k_0, \dots, k_{d-2}) is the last point in $HamPath_{\beta, d-1}$.

Now we define the random walk by describing how a particle may go from start to end. The path set is just all the possible paths the particle goes along. Intuitively, within one block, the last dimension $d - 1$ serves as the clock space. So as before, we perform one step of line walk (in the dimension which is the circularly next dimension of the last one that the walk just goes in), followed by two steps of walk in the clock space. If we run out of clock, we say we reach a boundary point at the current block, and we move to the next block via a path segment called block-changing segment. In what follows, we specify how the particle may move during the whole random walk process, including going through block-changing segments. We always use $x_0 \dots x_{d-1}$ to denote the current position of the particle, and assume $x_i = (k_i - 1)\alpha + y_i$, i.e. x is in the block (k_0, \dots, k_{d-2}) with the offsets (y_0, \dots, y_{d-1}) . Thus the instruction $x_0 = x_0 + 1$, for example, means that the particle moves from $x_0 \dots x_{d-1}$ to $(x_0 + 1)x_1 \dots x_{d-1}$.

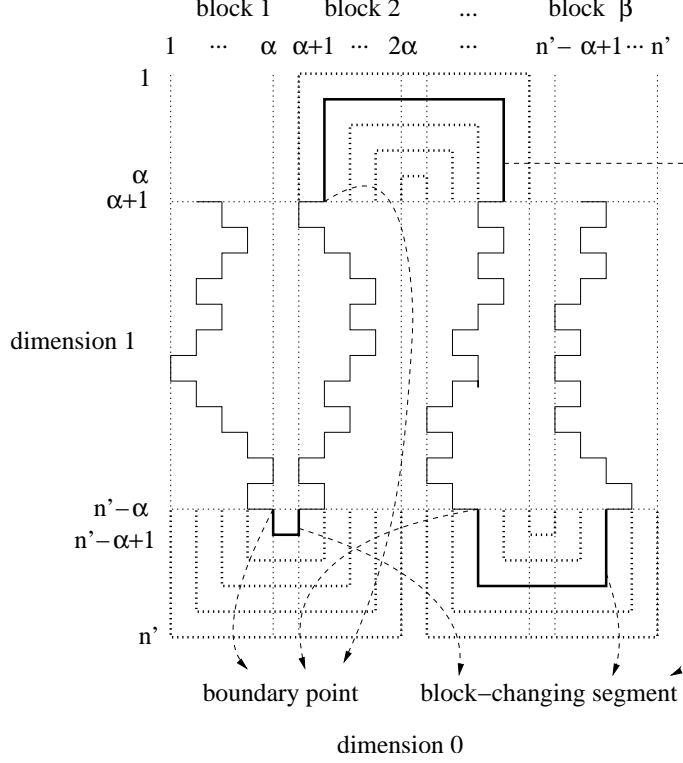


Figure 2: Illustration for changing a block in the 2-dimensional grid

1. Initially $x_0 = \dots = x_{d-2} = 0$, $x_{d-1} = \alpha + 1$, $k_0 = \dots = k_{d-2} = 1$.
2. **for** $t = 1$ **to** $(n' - 2\alpha)\beta^{d-1}$,
 Let $t' = \lfloor \frac{t-1}{n'-2\alpha} \rfloor$, $i = (t-1) \bmod (d-1)$
do either $x_i = \max\{x_i - 1, (k_i - 1)\alpha + 1\}$ or $x_i = \min\{x_i + 1, k_i\alpha\}$ randomly
if $t \neq k(n' - 2\alpha)$ for some positive integer k ,
 do $x_{d-1} = x_{d-1} + (-1)^{t'}$ twice
else (*the particle is now at a boundary point*)
 if the particle is not in the last block
 (Suppose the current block changes to the next block by increasing k_j by $b \in \{-1, 1\}$)
 do $x_{d-1} = x_{d-1} + (-1)^{t'}$ **for** $(\alpha + 1 - y_j)$ times
 do $x_j = x_j + b$ **for** $2(\alpha + 1 - y_j) - 1$ times
 do $x_{d-1} = x_{d-1} + (-1)^{t'+1}$ **for** $(\alpha + 1 - y_j)$ times
 $k_j = k_j + b$
 else
 The particle stops and the random walk ends

It is easy to verify that every boundary point has one unique block-changing segment, and different block-changing segments do not intersect. Also note that we do not let the clock tick when we are moving from one block to the another. Thus the block-changing segments thread all the blocks to form a $[\alpha]^{d-1} \times [L]$ grid, where $L = (n' - 2\alpha)\beta^{d-1}$. Actually, for our lower bound purpose, we can think of the random walk as performed in the product graph $[\alpha]^{d-1} \times [L]$. We will next make this clearer as below.

What we care about is, as before, the probability that the random walk starting from a point $x = x_0 \dots x_{d-1}$ passes another point $x' = x'_0 \dots x'_{d-1}$. Note that for any point x (including those on the

block-changing segments), there is only one time t when the walk may hit x , and this t is known by x itself. Similarly we use t' to denote the time when the path passes x' . Denote the probability that the random walk starting from x passes x' by $\mathbf{Pr}[x \rightarrow x']$. As before suppose $x_i = (k_i - 1)\alpha + y_i$ and $x'_i = (k'_i - 1)\alpha + y'_i$ for $i \in \{0, \dots, d-2\}$.

We first consider the case that one of the two points, say x' is on a block-changing segment. Since different block-changing segments never intersect, a path passes x' if and only if the path passes the boundary point x'' at the beginning of the block-changing segment that x' is in. Also note that the time that the path passes x'' is also t' because the time does not elapse on the block-changing segment. So it holds that $\mathbf{Pr}[x \rightarrow x'] = \mathbf{Pr}[x \rightarrow x'']$, and it is enough to consider the case that both x and x' are not in clock-changing segments.

Now suppose both x and x' are not in clock-changing segments. In general, x and x' may be not in the same block, so going from x to x' needs to change blocks. Recall that to change from the block (k_0, \dots, k_{d-2}) to the next one, only one k_i changes by increasing or decreasing by 1. Suppose that to go to x' from x , we change blocks for c times, by changing $k_{i_1}, k_{i_2}, \dots, k_{i_c}$ in turn. Let $n_j = |\{s \in [c] : i_s = j\}|$. Note that to get to x' from x after $t' - t$ steps, the coordinate j needs to be x'_j after $t' - t$ steps for each coordinate $j \in \{0, \dots, d-2\}$. It is not hard to see that if a block-changing needs to change k_j by increasing $b \in \{-1, 1\}$, then among all the offsets y_i 's, only the y_j gets changed, and the change is a reflection within the block. That is, suppose x_j is $(k_j - 1)\alpha + y_j$ before the block-changing, then x_j changes to $(k_j + b - 1)\alpha + (\alpha + 1 - y_j)$ after the block-changing. So if $c = 1$, then $\mathbf{Pr}[x \rightarrow x']$ is equal to the probability that a random walk in $[\alpha]^{d-1}$ starting from $y_0 \dots y_{d-2}$ hits $y''_0 \dots y''_{d-2}$ after exactly $t' - t$ steps, where $y''_j = y'_j$ if $j \neq i_1$ and $y''_{i_1} = \alpha + 1 - y'_{i_1}$. For general c , $\mathbf{Pr}[x \rightarrow x']$ is equal to the probability that a random walk in $[\alpha]^{d-1}$ starting from $y_0 \dots y_{d-2}$ hits $y''_0 \dots y''_{d-2}$ after exactly $t' - t$ steps, where $y''_j = y'_j$ if n_j is even and $y''_j = \alpha + 1 - y'_j$ if n_j is odd. Note that this probability has nothing to do with the block-changing; it is just the same as we have a clock space $[(n' - 2\alpha)\beta^{d-1}]$ to record the random walk on $[\alpha]^{d-1}$. Thus we can use Proposition 11 to upper bound this probability and just think of the graph as $[n^r]^{d-1} \times [L]$ and use Theorem 9, with $G^w = [n^r]^{d-1}$ and $G^c = [L]$.

Now we have $T = \lfloor L/2 \rfloor$ and $p_t = O(1/\sqrt{t^{d-1}})$ for $t \leq n^{2r}$ and $p_t = O(1/n^{r(d-1)})$ for $t > n^{2r}$. So for randomized lower bounds, if $d \geq 4$, then let $r = d/(2d-2)$ and we get

$$RLS([n]^d) = \Omega \left(n^{1+(1-r)(d-1)} / \left(\sum_{t=1}^{n^{d/(d-1)}} \frac{1}{\sqrt{t^{d-1}}} + \frac{n^{1+(1-r)(d-1)}}{n^{r(d-1)}} \right) \right) = \Omega(n^{d/2}). \quad (100)$$

If $d = 3$, let $r = 3/4 - \log \log n / (4 \log n)$, and we get $RLS([n]^3) = \Omega((n^3 / \log n)^{1/2})$. For $d = 2$, let $r = 2/3$ and we get $RLS([n]^2) = \Omega(n^{2/3})$.

For the quantum lower bounds, if $d \geq 6$, then let $r = 2d/(3d-3)$ and we get

$$QLS([n]^d) = \Omega \left(n^{1+(1-r)(d-1)} / \left(\sum_{t=1}^{n^{d/(d-1)}} \frac{1}{t^{(d-1)/4}} + \frac{n^{1+(1-r)(d-1)}}{n^{r(d-1)/2}} \right) \right) = \Omega(n^{d/3}). \quad (101)$$

If $d = 5$, then let $r = 5/6 - \log \log n / (6 \log n)$ and $QLS([n]^5) = \Omega((n^5 / \log n)^{1/3})$. For $2 \leq d \leq 4$, we let $r = d/(d+1)$, then $QLS([n]^d) = \Omega(n^{d/2-d/(d+1)})$, which is $\Omega(n^{1/3})$, $\Omega(n^{3/4})$, $\Omega(n^{6/5})$ for $d = 2, 3, 4$, respectively.

4.2.3 Further improvement on 2-dimensional grid $[n]^2$

Some other random walk may be used to further improve the lower bound on low dimension grid cases. Here is one way to improve $QLS([n]^2)$ from $\Omega(n^{1/3})$ to $\Omega(n^{4/5})$. We cut the graph $[n]^2$ into $n^{2/5}$ smaller grids, each of size $n^{4/5} \times n^{4/5}$. Without loss of generality, assume both $n^{1/5}$ and $n^{4/5}$ are integers, and further assume $n^{1/5} \equiv 3 \pmod{4}$; otherwise we can consider a slightly smaller grid by the simple trick as at the beginning of Section 4.2.2. We shall use a random walk similar to Aaronson's in [2] as follows in each block, and change blocks after each step. Thus different blocks to record different time.

For any time $t \in [n^{1/5}(n^{1/5} - 1)]$, suppose $t = 2rn^{1/5} + t'$ where $r \in \{0, 1, \dots, (n^{1/5} - 3)/2\}$ and $t' \in \{1, 2, \dots, 2n^{1/5}\}$. Let

$$u = \begin{cases} 0 & \text{if } t' \equiv 0, 1 \pmod{4} \\ n^{4/5} & \text{if } t' \equiv 2, 3 \pmod{4} \end{cases} \quad (102)$$

Let $block(t)$ as the small grid

$$\begin{cases} \{(x = (\lceil t'/2 \rceil - 1)n^{4/5} + x', y = 2rn^{4/5} + u + y') : x', y' \in [n^{4/5}]\} & \text{if } r \text{ is even} \\ \{(x = (n^{1/5} - \lceil t'/2 \rceil)n^{4/5} + x', y = 2rn^{4/5} + u + y') : x', y' \in [n^{4/5}]\} & \text{if } r \text{ is odd} \end{cases} \quad (103)$$

The (x', y') is called the offset of (x, y) . Now define the random walk as follows and as depicted in Figure 3.

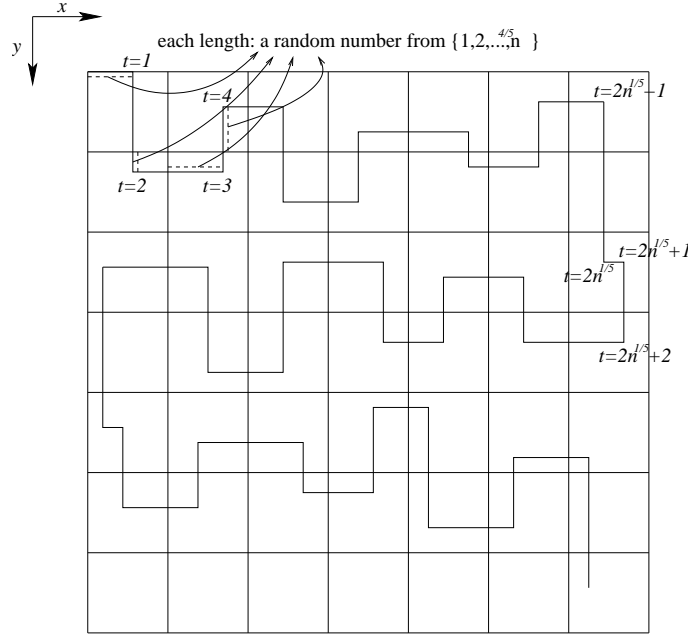


Figure 3: A different random walk in the 2 dimensional-grid

Initially $(x, y) = (1, 1)$
for $t = 1, 2, \dots, n^{1/5}(n^{1/5} - 1)$ (Suppose the current point is (x, y) with offset (x', y'))
 if t' is odd
 pick a random $x'' \in [n^{1/5}]$, move horizontally to the point in $block(t)$ with the offset (x'', y')
 else
 if $t' = 2n^{1/5}$ **then** $c = 1$ **else** $c = 0$
 pick a random $y'' \in [n^{1/5}]$, move vertically to the point in $block(t+c)$ with the offset (x', y'')

We then follow the same track as in the proof of Theorem 9. To get a reduction from Local Search on $[n]^2$ to the $Path_P$ problem, we define the function

$$f_X(v) = \begin{cases} |v - (1, 1)|_{[n]^2} & \text{if } v \notin set(X) \\ -2n^{4/5}(t-1) - (-1)^r x'_v + (-1)^{\lceil t'/2 \rceil} y'_v & \text{if } v \in set(X) \cap block(t) \end{cases} \quad (104)$$

Intuitively, the function value decreases along the path as before. But the decrement is not always by 1: each block has its fixed value setting. If for example the path passes through the block toward

right and down (as in the first block), then the value $-x' - y'$ is used within the block. In this way, we do not need to know the length of the path segment from top to v to calculate each $f_X(v)$.

What we care about is still, as in Equality (34), the probability that the path X' passes another point x on X , under the condition that $X' \wedge Y = k'$. It is not hard to see that this probability is $\Theta(1)$ in general if x is in $block(k')$, and $\Theta(1/n^{4/5})$ otherwise (*i.e.* when x is in $block(t)$ for some $t > k'$). Thus by $L = \Theta(n^{2/5})$ we have

$$QLS([n]^2) = \Omega\left(n^{2/5} / \left(1 + n^{2/5} / \sqrt{n^{4/5}}\right)\right) = \Omega(n^{2/5}) \quad (105)$$

This completes the proof of Theorem 3.

Note that this random walk suffers from the fact that the “passing probability” is now $n^{4/5}$ times the “hitting probability”. So for general d , we can get $RLS([n]^d) = \Omega(n^{d/(d+1)})$ and $QLS([n]^d) = \Omega(n^{d/(2d+1)})$, which only gives better results for QLS on the 2-dimensional grid.

5 New algorithms for Local Search on general graphs

In [4, 2], a randomized and a quantum algorithm for Local Search on general graphs are given as follows. Do a random sampling over all the vertices, find a vertex v in them with the minimum f -value. (For the minimum f -value finding procedure, The randomized algorithm in [4] just queries all these vertices and find the minimum, while the quantum algorithm in [2] uses the algorithm by Durr and Hoyer [11] based on Grover search [12] to get a quadratic speedup.) If v is a local minimum, then return v ; otherwise we follow a *decreasing path* as follows. Find a neighbor of v with the minimum f -value, and continue this minimum-value-neighbor search process until getting to a local minimum. We can see that the algorithms actually fall into the generic algorithm category (see Section 1), with the initial point picked as the best one over some random samples.

In this section, we give new randomized and quantum algorithms, which work better than this simple “random sampling + steepest descent” method when the graph expands slowly. Here the idea is that after finding the minimum vertex v of the sampled points, instead of following the decreasing path of v , we start over within a smaller range, which contains those vertices “close to” v . If this smaller range contains a local minimum for sure, then we can simply search a local minimum in it and do this procedure recursively. But one caveat here is that a straightforward recursion does not work, because a local minimum u in the smaller range may be not a local minimum in the original larger graph G (since u may have more neighbors in G). So we shall find a small range which has a “good” boundary in the sense that all vertices on the boundary have a large f -value.

Now we describe the algorithm precisely, with some notations as follows. For $G = (V, E)$, a given function $f : V \rightarrow \mathbb{N}$, a vertex $v \in V$ and a set $S \subseteq V$, let $n(v, S) = |\{u \in S : f(u) < f(v)\}|$. The boundary $B(S)$ of the set $S \subseteq V$ is defined by $B(S) = \{u \in S : \exists v \in V - S \text{ s.t. } (u, v) \in E\}$. In particular, $B(V) = \emptyset$. A decreasing path from a vertex $v \in V$ is a sequence of vertices v_0, v_1, \dots, v_k such that $v_0 = v$, v_k is a local minimum and $f(v_{i+1}) = \min_{v:(v_i,v) \in E} f(v) < f(v_i)$ for $i = 0, \dots, k-1$. We write $f(u) \leq f(S)$ if $f(u) \leq f(v)$ for all $v \in S$. In particular, it always holds that $f(u) \leq f(\emptyset)$. Suppose $d = \max_{u,v \in V} |u - v|$ is the diameter of the graph, and $\delta = \max_{v \in V} |\{u : (u, v) \in E\}|$ is the max degree of the graph. In the following algorithm, the asymptotical numbers at the end of some command lines are the numbers of randomized or quantum queries needed for the step. For those commands without any number, no query is needed.

1. $m_0 = d$, $U_0 = V$;
2. $i = 0$;
3. **while** ($|m_i| > 10$) **do**
 - (a) Randomly pick (with replacement) $\lceil \frac{8|U_i|}{m_i} \log \frac{1}{\epsilon_1} \rceil$ vertices from U_i , where $\epsilon_1 = 1/(10 \log_2 d)$;
 - (b) Search the sampled vertices for one v_i with the minimal f value.
 - Randomized algorithm: query all the sampled vertices and get v_i . $— O\left(\frac{8|U_i|}{m_i} \log \frac{1}{\epsilon_1}\right)$

- Quantum algorithm: use Durr and Hoyer's algorithm [11] with the error probability at most $\epsilon_2 = 1/(10 \log_2 d)$. — $O\left(\sqrt{\frac{8|U_i|}{m_i} \log \frac{1}{\epsilon_1} \log \frac{1}{\epsilon_2}}\right)$
- (c) **if** $i = 0$, **then** $u_{i+1} = v_i$;
else if $f(u_i) \leq f(v_i)$, **then** $u_{i+1} = u_i$;
else $u_{i+1} = v_i$;
- (d) **for** $j = 1, 2, \dots$
 - i. Randomly pick $m_{ij} \in M_i = \{m : m_i/8 \leq m \leq m_i/2, |W(m)| \leq 10|U_i|/m_i\}$, where $W(m) = \{w \in U_i : |w - u_{i+1}| = m\}$. Let $W_{ij} = W(m_{ij})$.
 - ii. Test whether $f(u_{i+1}) \leq f(W_{ij})$
 - Randomized algorithm: query all vertices in W_{ij} . — $O(|W_{ij}|)$
 - Quantum algorithm: use Durr and Hoyer's algorithm [11] on W_{ij} with the error probability at most $\epsilon_3 = 1/(200 \log_2 d)$. — $O\left(\sqrt{|W_{ij}|} \log \frac{1}{\epsilon_3}\right)$
 - iii. If the answer is Yes, jump out of this **for** loop and go to Step 3e.
- (e) $J_i = j$, $m_{i+1} = m_{ij}$, $W_i = W_{ij}$, $U_{i+1} = \{u \in U_i : |u - u_{i+1}| \leq m_{i+1}\}$;
- (f) $i = i + 1$;
- 4. $I = i$;
- 5. Follow a decreasing path of u_I to find a local minimum.
 - Randomized algorithm: in each step, query all the neighbors — $O(\delta)$
 - Quantum algorithm: in each step, use Durr and Hoyer's algorithm with the error probability at most $1/100$ — $O(\sqrt{\delta})$

Define $c(k) = \max_{v \in V} |\{u : |u - v| \leq k\}|$. Apparently, the expanding speed of a graph is upper bounded by $c(k)$. The following theorem says that the algorithm is efficient if $c(k)$ is small.

Theorem 12 *The algorithm outputs a local minimum with probability at least $1/2$. The randomized algorithm uses $O\left(\sum_{i=0}^{I-1} \frac{c(m_i)}{m_i} \log \log d\right)$ queries in expectation, and the quantum algorithm uses $O\left(\sum_{i=0}^{I-1} \sqrt{\frac{c(m_i)}{m_i}} (\log \log d)^{1.5}\right)$ queries in expectation.*

In case that $c(k) = O(k^\alpha)$ for some $\alpha \geq 1$ and $k = 1, \dots, d$, the expected number of queries that the randomized algorithm uses is $O\left(\frac{d^{\alpha-1}-1}{1-2^{1-\alpha}} \log \log d\right)$ if $\alpha > 1$ and $O(\log d \log \log d)$ if $\alpha = 1$. The expected number of queries that the quantum algorithm use is $O\left(\frac{d^{\frac{\alpha-1}{2}}-1}{1-2^{\frac{1-\alpha}{2}}} (\log \log d)^{1.5}\right)$ if $\alpha > 1$ and $O(\log d \log \log d)$ if $\alpha = 1$.

Several comments before proving the theorem:

1. $\lim_{\alpha \rightarrow 1} \frac{d^{\alpha-1}-1}{1-2^{1-\alpha}} = \lim_{\alpha \rightarrow 1} \frac{d^{\frac{\alpha-1}{2}}-1}{1-2^{\frac{1-\alpha}{2}}} = \log_2 d$
2. If $\alpha - 1 \geq \epsilon$ for some constant $\epsilon > 0$, then $\frac{d^{\alpha-1}-1}{1-2^{1-\alpha}} = \Theta(d^{\alpha-1})$ and $\frac{d^{\frac{\alpha-1}{2}}-1}{1-2^{\frac{1-\alpha}{2}}} = \Theta(d^{(\alpha-1)/2})$.
If further the bound $c(k) = O(k^\alpha)$ is tight in the sense that $N = c(d) = \Theta(d^\alpha)$, then $RLS(G) = O\left(\frac{N}{d} \log \log d\right)$ and $QLS(G) = O\left(\sqrt{\frac{N}{d}} (\log \log d)^{1.5}\right)$.
3. For 2-dimensional grid, $d = \Theta(n)$ and $\alpha = 2$. Thus Theorem 5 follows immediately.

Proof We shall prove the theorem for the quantum algorithm. The analysis of the randomized algorithm is almost the same (and actually simpler). We say W_i is *good* if $f(u_{i+1}) \leq f(W_i)$. We shall first prove the following claim, then the theorem follows easily.

Claim 3 *For each $i = 0, 1, \dots, I-1$, the following three statements hold.*

1. $n(u_{i+1}, U_{i+1}) \leq n(u_{i+1}, U_i) \leq m_i/8 \leq m_{i+1}$ with probability $1 - \epsilon_1 - \epsilon_2$.

2. If $n(u_{i+1}, U_i) \leq m_i/8$, then W_i is good with probability $1 - \epsilon_3 J_i$, and $\mathbf{E}[J_i] \leq 2$.
3. If W_0, \dots, W_i are all good, then $f(u_{i+1}) \leq f(B(U_{i+1}))$, and $u_{i+1} \notin B(U_{i+1})$.

Proof 1: In Step 3a - 3c, denote by S the set of the $\lceil \frac{8|U_i|}{m_i} \log \frac{1}{\epsilon_1} \rceil$ sampled vertices in Step 3a. Let $a = \min_{u \in S} f(u)$, then $|\{v \in U_i : f(v) < a\}| \leq m_i/8$ with probability at least $1 - \epsilon_1$. The v_i found in Step 3b achieves the minimum in the definition of a with probability at least $1 - \epsilon_2$. Put the two things together, we have $n(v_i, U_i) \leq m_i/8$ with probability at least $1 - \epsilon_1 - \epsilon_2$. Since $f(u_{i+1}) \leq f(v_i)$ (by Step 3c), $U_{i+1} \subseteq U_i$ (by Step 3e) and $m_{i+1} \geq m_i/8$ (by Step 3(d)i), we have $n(u_{i+1}, U_{i+1}) \leq n(u_{i+1}, U_i) \leq n(v_i, U_i) \leq m_i/8 \leq m_{i+1}$ with probability at least $1 - \epsilon_1 - \epsilon_2$.

2: We say an m_{ij} is good if the corresponding W_{ij} is good, i.e. $f(u_{i+1}) \leq f(W_{ij})$. Note that for any $m_{ij} \in [m_i]$, we have $W_{ij} \subseteq U_i$, and also have $W_{ij} \cap W_{ij'} = \emptyset$ if $m_{ij} \neq m_{ij'}$. Therefore, if $n(u_{i+1}, U_i) \leq m_i/8$, then at most $m_i/8$ distinct m_{ij} 's in $[m_i]$ are *not* good. Also note that the number of distinct m_{ij} 's s.t. $|W(m_{ij})| > 10|U_i|/m_i$ is less than $m_i/10$. Therefore, $|M_i| \geq (\frac{3}{8} - \frac{1}{10})m_i > m_i/4$. So if $n(u_{i+1}, U_i) \leq m_i/8$, a random m_{ij} in M_i is good with probability at least $1/2$, and thus $\mathbf{E}[J_i] \leq 2$. Also the probability that all the Grover searches in Step 3(d)ii are correct is at least $1 - J_i \epsilon_3$.

3: We shall first prove $B(U_{i+1}) \subseteq B(U_i) \cup W_i$. In fact, any $s \in B(U_{i+1})$ satisfies that $s \in U_{i+1}$ and that $\exists t \in V - U_{i+1}$ s.t. $|s - t| = 1$. Recall that $U_{i+1} \subseteq U_i$, so if $t \in V - U_i$, then $s \in B(U_i)$ by definition. Otherwise $t \in U_i - U_{i+1}$, and thus $t \in U_i$ and $|t - u_{i+1}| > m_{i+1}$ by the definition of U_{i+1} . Noting that $|s - u_{i+1}| \leq m_{i+1}$ since $s \in U_{i+1}$, and that $|s - t| = 1$, we have $|s - u_{i+1}| = m_{i+1}$, which means $s \in W_i$. Thus for all $s \in B(U_{i+1})$, either $s \in B(U_i)$ or $s \in W_i$ holds, which implies $B(U_{i+1}) \subseteq B(U_i) \cup W_i$.

Applying the result recursively, we have $B(U_{i+1}) \subseteq B(U_0) \cup W_0 \cup \dots \cup W_i = W_0 \cup \dots \cup W_i$. Since we have $f(u_{i+1}) \leq f(u_i) \leq \dots \leq f(u_1)$ (by Step 3c) and $f(u_{k+1}) \leq f(W_k)$ (for $k = 0, \dots, i$) by the assumption that all W_k 's are good, we know that $f(u_{i+1}) \leq f(W_0 \cup \dots \cup W_i)$, which implies $f(u_{i+1}) \leq f(B(U_{i+1}))$.

For the other goal $u_{i+1} \notin B(U_{i+1})$, it is sufficient to prove $u_{i+1} \notin B(U_i)$ and $u_{i+1} \notin W_i$. The latter is easy to see by the definition of W_i . For the former, we can actually prove $u_{k+1} \notin B(U_k)$ for all $k = 0, \dots, i$ by induction on k . The base case of $k = 0$ is trivial because $B(U_0) = \emptyset$. Now suppose $u_k \notin B(U_{k-1})$. There are two cases of u_{k+1} by Step 3c. If $f(u_k) \leq f(v_k)$, then $u_{k+1} = u_k \notin B(U_{k-1})$ by induction. Again by the definition of W_{k-1} we know that $u_k \notin W_{k-1}$ and thus $u_{k+1} = u_k \notin B(U_k)$. The other case is $f(u_k) > f(v_k)$, then $u_{k+1} = v_k$, and therefore $f(u_{k+1}) = f(v_k) < f(u_k) \leq f(B(U_k))$ (by the first part in 3), which implies that $u_{k+1} \notin B(U_k)$. \square

(Continue the proof of Theorem 12) Now by the claim, we know that with probability at least $1 - I(\epsilon_1 + \epsilon_2) - \sum_{i=0}^{I-1} J_i \epsilon_3$, we will have that

$$n(u_I, U_I) \leq m_I, \quad f(u_I) \leq f(B(U_I)), \quad u_I \notin B(U_I). \quad (106)$$

Note that the correctness of the algorithms follows from these three items. Actually, by the last two items, we know that any decreasing path from u_I is contained in U_I . Otherwise suppose $(u_I^0, u_I^1, \dots, u_I^T)$ is a decreasing path from u_I (so $u_I^0 = u_I$), and the first vertex out of U_I is u_I^t , then $u_I^{t-1} \in B(U_I)$. Since $u_I^0 \notin B(U_I)$, we have $t - 1 > 0$ and thus $f(u_I^{t-1}) < f(u_I)$, contradicting to $f(u_I) \leq f(B(U_I))$. Now together with the first item, we know that any decreasing path from u_I is no more than m_I long. Thus Step 5 will find a local minimum by following a decreasing path.

The error probability of the algorithm is $I(\epsilon_1 + \epsilon_2) + J\epsilon_3 + 10/100$, where $J = \sum_{i=0}^{I-1} J_i$. Since $\mathbf{E}[J] = 2I$, we know by Markov inequality that with $J < 20I$ with probability at least $9/10$. Since $\epsilon_1 = \epsilon_2 = 1/(10 \log_2 d)$ and $\epsilon_3 = 1/(200 \log_2 d)$, and note that $I \leq \log_2 d$ because $m_0 = d$ and $m_{i+1} \leq \lceil m_i/2 \rceil$. So the total error probability is less than $1/2$.

We now consider the number of queries used in the i -th iteration. Note from Step 1 and Step 3e that $|U_i| \leq c(m_i)$ for $i = 0, 1, \dots, I - 1$. So Step 3b uses

$$O\left(\sqrt{\frac{8|U_i|}{m_i}} \log \log d \log \log d\right) = O\left(\sqrt{\frac{c(m_i)}{m_i}} (\log \log d)^{1.5}\right) \quad (107)$$

queries. Also note from Step 3(d)i that $|W_{ij}| \leq 10|U_i|/m_i$, so Step 3d uses $O(\sum_{j=1}^{J_i} \sqrt{c(m_i)/m_i} \log \log d)$ queries, which has the expectation of $O(\sqrt{c(m_i)/m_i} \log \log d)$. Finally, Step 5 uses $O(\sqrt{\delta})$ queries. Note that $\delta = c(1) = O(c(m_I)/m_I)$ where m_I is a constant integer in the range $[6, 10]$. Altogether, the total expected number of queries used is

$$O \left(\left(\sum_{i=0}^{\log_2 d - 1} \sqrt{c(m_i)/m_i} \right) (\log \log d)^{1.5} \right). \quad (108)$$

If $c(k) = O(k^\alpha)$ for some $\alpha \geq 1$ and $k = 1, \dots, d$, then

$$\sum_{i=0}^{\log_2 d - 1} \sqrt{\frac{c(m_i)}{m_i}} = \sum_{i=0}^{\log_2 d - 1} m_i^{(\alpha-1)/2} = \sum_{i=0}^{\log_2 d - 1} (d/2^i)^{(\alpha-1)/2} = \frac{d^\beta - 1}{1 - 2^{-\beta}} \quad (109)$$

where $\beta = (\alpha - 1)/2$. This completes the proof for the quantum algorithm, except that in the case of $\alpha = 1$ we only have a quantum upper bound of $O(\log d (\log \log d)^{1.5})$. But note that the randomized algorithm uses $O(\log d \log \log d)$ queries (because of the saving at error probability controls). So when $\alpha = 1$, the quantum algorithm just uses the randomized one. \square

6 Open problems: remaining gaps

We list those grids on which the query complexities of Local Search still have gaps.

$d =$	2	3
old RLS	$[\Omega(1), O(n)]$	$[\tilde{\Omega}(\sqrt{n}), O(n^{\frac{3}{2}})]$
new RLS	$[\Omega(n^{\frac{2}{3}}), O(n)]$	$[\Omega(n^{\frac{2}{3}}/(\log n)^{\frac{1}{2}}), O(n^{\frac{3}{2}})]$
remaining gap	$n^{\frac{1}{3}} (= N^{\frac{1}{6}})$	$(\log n)^{\frac{1}{2}} (= (\log N)^{\frac{1}{2}})$

$d =$	2	3	4	5
old QLS	$[\Omega(n^{\frac{1}{4}}), O(n^{\frac{2}{3}})]$	$[\tilde{\Omega}(n^{\frac{1}{4}}), O(n)]$	$[\tilde{\Omega}(n^{\frac{1}{2}}), O(n^{\frac{4}{3}})]$	$[\tilde{\Omega}(n^{\frac{4}{5}}), O(n^{\frac{5}{3}})]$
new QLS	$[\Omega(n^{\frac{2}{5}}), O(n^{\frac{1}{2}})]$	$[\Omega(n^{\frac{2}{4}}), O(n)]$	$[\Omega(n^{\frac{5}{6}}), O(n^{\frac{4}{3}})]$	$[\Omega(n^{\frac{5}{3}}/(\log n)^{\frac{1}{3}}), O(n^{\frac{5}{3}})]$
remaining gap	$n^{\frac{1}{10}} (= N^{\frac{1}{20}})$	$n^{\frac{1}{4}} (= N^{\frac{1}{12}})$	$n^{\frac{2}{15}} (= N^{\frac{1}{30}})$	$(\log n)^{\frac{1}{3}} (= (\log N)^{\frac{1}{3}})$

where $N = n^d$ is the number of the vertices in the grid.

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